

Application of Assessment Generation System

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ABSTRACT

Online education and online assessments have become increasingly common in recent years. This study first investigates student satisfaction with online learning at Eastern Mediterranean University and compares their academic performance during online learning to their performance in a traditional, in-person learning environment. A total of 1087 students participated in an online survey and the results suggest that students have a high level of satisfaction with online learning, although their academic performance showed a slight drop compared to in-person learning. In order to further improve the effectiveness of online education, this research proposes a question bank system that uses a modified NSGA-II algorithm to select questions tailored to individual students and instructors' needs. The modified NSGA-II algorithm is efficient and accurate, and meets the specified requirements for difficulty level and duration. By using proposed question bank, educators can provide a more targeted and effective learning experience for their students, including through the use of online assessments. These findings can provide valuable insights for policymakers seeking to improve the quality of online education and support student success.

Keywords: Online assessment, Educational technology, Multi-objective optimization, Question bank, E-learning.

ÖZ

Son yılların trendleri arasında online eğitim ve online değerlendirme yöntemlerinin yaygınlaşması yer almaktadır. Bu çalışma, Doğu Akdeniz Üniversitesi'nde öğrencilerin yüz yüze ve online öğrenme ortamlarından memnuniyet düzeylerini ve bu ortamların akademik performans üzerindeki etkisini karşılaştırmaktadır. Çalışmaya online anket yoluyla 1087 öğrenci katılmıştır ve sonuçlar, öğrencilerin online öğrenme ortamından memnun olduklarını ancak yüz yüze eğitim ortamına göre performanslarında hafif bir düşüş olduğunu göstermektedir. Online eğitimin etkinliğini artırmak amacıyla, bu çalışma öğrencilerin ihtiyaçlarına ve yeteneklerine uygun soruları seçmek için bir kişiselleştirilmiş soru bankası sistemi önermektedir. Bu sistemde, geliştirilmiş NSGA-II algoritması kullanılmaktadır ve bu algoritma zorluk seviyesi ve süre gibi belirtilen gereksinimleri karşılar şekilde etkili ve doğru çalışmaktadır. Kişiselleştirilmiş soru bankası kullanımı sayesinde, eğitimciler öğrencilerine daha hedeflenmiş ve etkili bir öğrenme deneyimi sunabilirler. Bu bulgular, online eğitimin kalitesini artırmak ve öğrenci başarısını desteklemek amacıyla yöneticiler için değerli fikirler sunabilir.

Anahtar Kelimeler: Online değerlendirme, Eğitim teknolojisi, Çok amaçlı optimizasyon, Soru bankası, E-öğrenme.

To My Family

For your constant love and support

Specially my cute nephew Aynur

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AGE-MOEA	Adaptive Generational Replacement Multi-Objective Evolutionary Algorithm
ANOVA	Analysis of Variance
CBT	Computer-Based Test
CI	Continuance Intention to Use Online Learning
CoHE	Presidency of the Council of Higher Education
COVID-19	Coronavirus Disease 2019
CSS	Cascading Style Sheets
EA	Evolutionary Algorithm
ER-NSGA-II	Eligibility Ranking Non-Dominated Sorting Genetic Algorithm II
ET	Execution Time
F	Objective Function Value
GA	Genetic algorithm
GPA	Grade Point Average
HSD	Honestly Significant Difference
HTML	Hypertext Markup Language
HTTPS	Hypertext Transfer Protocol Secure
ID	Identification
IT	Information Technology
ITS	Intelligent Tutoring System
LMS	Learning Management Systems
MANOVA	Multivariate Analysis of Variance

MOACO	Multi- Objective Ant Colony Optimization
MOEA	Multi- Objective Evolutionary Algorithm
MOGA	Multi- Objective Genetic Algorithm
MOO	Multi- Objective Optimization
MOOP	Multi- Objective Optimization Problem
MOPSO	Multi-Objective Particle Swarm Optimization
NG	Number of Generations
NSGA-II	Non-Dominated Sorting Genetic Algorithm
OS	Online Learning Satisfaction
PCA	Principal Component Analysis
PhD	Doctor of Philosophy
PHP	Hypertext Preprocessor
PSO	The Particle Swarm Optimization
RAM	Random Access Memory
SDLC	System Development Life Cycle
SMS-EMOA	S-Metric Selection Evolutionary Multi-Objective Optimization Algorithm
SP	Students' Preference Between Face-to-Face and Online Education
SPSS	Statistical Package for the Social Sciences
SQL	Structured Query Language
UI	User Interface
W	Weight Coefficient
WBT	Web-Based Test
WHO	World Health Organization
WRS	Weighted Random Sampling

Chapter 1

INTRODUCTION

1.1 Overview

Online learning has become increasingly popular in recent years, providing learners with the flexibility to study at their own pace and from the comfort of their own homes. However, one challenge that has emerged with the growth of online learning is the quality and appropriateness of online assessments. In order to address this issue, we have conducted research on the design and development of a question bank system that uses our presented modified NSGA-II multi-objective optimization method to extract questions for a given topic or subject area. This question bank system is able to select the most relevant, high-quality, and appropriate questions for the intended audience, maximizing the value of students' study time.

Prior to plan this system, we conducted preliminary research and analysis on students' perception of online learning in order to identify weaknesses. Our analysis revealed that online learning needs to improve in many areas especially in assessment field in order to provide a more effective and engaging experience for students.

The question bank can be used for a variety of purposes, such as studying for exams, generating an exam paper, or just learning more about a particular subject. By using the optimization method, the system is able to select the most relevant and high-quality questions in optimal period of time.

1.2 Background and Problem Statement

A question bank is a system that allows users to practice and assess their knowledge in a particular subject or skill area. The system includes a database of questions and answers and a user interface that allows users to generate sets of questions based on their desired content area, difficulty level, and total duration.

Traditionally, question banks have been used in education and training settings as a tool for practice and assessment. However, traditional question banks often lack customization and personalization, which can limit their effectiveness for individual learners. Question bank systems have the potential to improve learning outcomes by tailoring the content and difficulty level of the questions to the individual user.

One of the challenges of online learning is the quality and appropriateness of online assessments. Many online assessments are poorly written or unrelated to the subject matter being taught, leading to a suboptimal learning experience for students. In order to address this issue, there is a need for a tool that can extract reliable, relevant, high-quality, and appropriate questions for online assessments.

1.3 History Overview

Computers have become an integral part of our daily lives, impacting various aspects of our lives. This shift in the role of computers in various applications can be traced back to the late 1970s. Since then, computers have played a significant role in the world, particularly in education. In addition to being used as a teaching tool both in traditional and distance education settings, computers have also been utilized to provide alternative testing options for educators.

Online assessment systems have a long history, dating back to the early days of computer-based testing in the 1970s [1]. At this time, the use of computers for testing was primarily limited to multiple-choice tests, which could be easily scored by the computer. However, as computers became more powerful and sophisticated, it became possible to develop more advanced assessment systems that could evaluate a wider range of learner responses.

One of the earliest examples of an online assessment system was the Intelligent Tutoring System (ITS), which was developed in the 1970s [2]. ITS used artificial intelligence techniques, such as expert systems and natural language processing, to provide personalized feedback and guidance to learners. These systems were designed to adapt to the individual needs and abilities of learners, by adjusting the difficulty of the assessment tasks accordingly. However, these early systems were limited by the computational power and storage capacity of the computers that were available at the time, and they were only able to assess a limited range of knowledge and skills.

In the 1990s, the widespread adoption of the Internet and the development of web-based technologies revolutionized the field of online assessment [3]. These technologies made it possible to deliver assessments to learners over the Internet, and to collect and analyze data on learner performance in real-time. This led to the development of a wide range of online assessment systems, including adaptive testing systems, which adjust the difficulty of the assessment tasks based on the learner's performance, and performance-based assessment systems, which evaluate the learner's ability to complete complex tasks or projects.

In recent years, there has been a growing interest in the use of question bank systems as a way to generate customized assessments for learners. These systems use artificial intelligence techniques to generate personalized questions for each learner, based on their individual strengths and weaknesses. Question bank systems have the potential to provide more targeted and effective assessments, and have been shown to improve learning outcomes in a variety of settings.

1.4 Related Works

There has been a growing body of research on online assessment and question bank systems in recent years. Question bank systems have also been the subject of a number of studies in recent years. These studies have generally found that question bank systems are effective at improving learning outcomes [4], particularly when used in combination with other types of assessments. However, there are also challenges associated with these systems, including the need for large amounts of data to train the system, and the difficulty of explaining the decision-making process of these systems to learners and educators. In [5], authors developed a computer-based learning system that included a self-assessment feature to improve students' learning outcomes. This self-assessment feature was equipped with item pools, which allowed teachers to easily administer and construct exams through the internet. The authors highlighted the benefits of item pools, including the ability for teachers to incorporate large question banks from textbook publishers and load them efficiently, as well as the convenience of being able to check understanding of learning materials at any time. In [6], authors developed an assessment system that used the Triple-A Model (assembling, administering, and appraising) as the foundation for providing the most comprehensive form of Computer-Based Test (CBT) or Web-Based Test (WBT) specifically for teacher education. In a different study, a web-based online examination system

proposed that is able to administer and automatically grade exams for students. This system allows for the conduct of exams, collection of answers, automatic marking of submissions, and generation of reports for the test. It supports various types of questions and can be accessed via the internet, making it suitable for both in-person and remote exams [7]. In [8], an adaptive question bank development and management system designed. There have been multiple online programs developed for creating question banks and evaluating student performance online. These online programs have been widely adopted in both traditional and distance education settings, as they provide a convenient and efficient way to assess student learning. There are several commercial products available that offer online questioning and evaluation systems, such as WebAssign and WebCT [9]. These systems provide immediate feedback on each question attempted. Moodle as a widely-used open-source learning management system is another important online assessment tool. It supports a range of online assessments, including multiple-choice tests, essay questions, and performance-based tasks, and has been shown to improve learning outcomes and student engagement in various educational contexts, though there are also limitations and challenges to consider in its use for online assessment [10].

1.5 The objectives with Specific Aims and Possible Outcomes

The main objective of this project is to provide a tool that can extract reliable, relevant, high-quality, and appropriate questions for online assessments for improving the effectiveness and engagement of online learning.

1.5.1 Objectives with Specific Aims

- Analysis of the weaknesses of online learning and assessments.
- The ability to collect the questions into the question bank.

- The ability to extract questions at an appropriate difficulty level and total duration using multi-objective optimization methods.

1.5.2 Possible Outcomes

- Increased relevance and usefulness of online assessments for learners and instructors.
- Improved quality of online assessments, leading to a more engaging and effective learning experience.
- A system to automate the process of exam paper generation with lesser manpower, time, energy, and money.

1.6 Significance of the Project

The proposed question bank system has the potential to significantly improve the effectiveness and engagement of online learning in several ways:

- Improved relevance of online assessments: By extracting relevant questions for a given topic or subject area, the system can ensure that online assessments are more useful and applicable to the intended audience. This can increase the perceived value of online learning for learners, leading to a more engaged and motivating learning experience.
- Improved quality of online assessments: By extracting high-quality questions, the system can ensure that online assessments are well-written and thoughtfully constructed, leading to a more engaging and effective learning experience.
- Improved appropriateness of online assessments: By extracting questions at an appropriate difficulty level and with a reasonable duration, the system can ensure that online assessments are appropriately challenging and manageable

for the intended audience. This can help to prevent frustration or disengagement due to excessively difficult or time-consuming assessments.

- Increased efficiency of online learning: By providing a tool that can extract high-quality and appropriate questions quickly and efficiently, the question bank system can help to streamline the process of creating and administering online assessments. This can save time and resources for educators, allowing them to focus on other aspects of teaching and learning.

1.7 Outline

This thesis consists of five chapters. The first chapter presents an overview of the background and problem statement, a review of related works, and the project's objective with specific aims and possible outcomes. The significance of the project is also discussed.

The chapter 2 examines the impact of the COVID-19 pandemic on the academic performance and perceptions of students towards online learning at a large public university in Northern Cyprus. It also reviews the concept of multi-objective optimization and its techniques and approaches.

This chapter 3 covers the design and development of a question bank system, including the identification of system actors, modeling of system requirements, application and database design, data collection, and the application of the modified NSGA-II algorithm for question set generation. It also mentions the technical aspects and user interface of the system.

This chapter 4 presents the testing and evaluation of the question bank system, including the experiment environment. It discusses the results of the experiment and identifies any drawbacks, as well as outlining planned improvements for the system.

In Chapter 5, the challenges and discussions of the study are explored and the significant aspects of the goals accomplished are emphasized. A general overview of the study is presented in this chapter summing up the thesis results and conclusion. It also outlines potential future work in the field.

Finally, five appendices are included. The appendices provide additional details and materials related to the study, including the survey details (Appendix A), the question bank system (Appendix B), and the Research and Publication Ethics Board approval (Appendix C).

Chapter 2

PRELIMINARIES

2.1 Students' Academic Performance and Perceptions towards Online Learning during the COVID-19 Pandemic at a Large Public University in Northern Cyprus

2.1.1 Introduction

The acute respiratory disease, which emerged as the Coronavirus (COVID-19) in Wuhan, China, in December 2019, has spread rapidly around the world. Due to this, the World Health Organization (WHO) declared the situation a pandemic on 11 March 2020. After the WHO's declaration of the pandemic, life began to change in many countries. The COVID-19 pandemic has affected numerous aspects of life and impacted the delivery of knowledge and skills at education levels [11]. The COVID-19 pandemic had a big and immediate effect on higher education, forcing universities to shift from traditional face-to-face to online learning [12]. Eastern Mediterranean University also decided to replace online learning with face-to-face education in March 2020 temporarily. This decision was faced with challenges that the examination of the student's perceptions towards these changes will present the university to improve the quality of education and prepare for possible similar situations in the future.

Britannica defines online learning as a “form of education in which the main elements include physical separation of teachers and students during instruction and the use of

various technologies to facilitate student-teacher and student-student communication” [13]. Online learning has been advantageous to its users, like making communication easier between instructors and students [14]. Other advantages of online learning include feasibility, flexibility, and accessibility can help students to continue their learning in any situation [15]. On the other hand, accessing the technologies is stated as a challenge for online learning. Lack of social interaction among students and poor learning outcomes can be considered as other challenges for online learning [16]. It should also be borne in mind that students in some fields of study which require face-to-face learning will lack some skills when entering their profession [11]. Various studies predict that online learning will be as effective as traditional face-to-face learning [17], [18]. Examining students’ academic performances and their level of satisfaction with online learning can inform the universities about the challenges facing online learning and take steps to solve them. Universities must ensure high levels of student satisfaction to improve the quality of education and attract students to participate in courses. Several studies show the relationship between the quality of online education and the level of satisfaction [19]. The level of satisfaction with online education, which is measured by criteria such as users’ perception of usability, the quality of the system or platform used, and the expected academic achievements, is the most important parameter in the success of online education [20].

2.1.2 Literature Review

Since the beginning of the Covid-19 pandemic, many educational institutions have been forced to temporarily replace traditional education with online education [21]. However, there were significant challenges. Some students had problems with technology use, mental health, time management, and balancing personal and academic life [22]. In some cases, motivation, self-efficacy, or cognitive engagement

were reduced, and technology use increased [23]. Research has also been conducted on the negative and positive aspects of online education, which has considered the decrease in concentration [22], loss of motivation [24]–[26], social isolation [25], [27], [28], and decrease in the interaction between teachers and students [24], [27] as negative effects. In contrast, flexibility in time and space [25], [27]–[30], ease of access to resources and materials [27], [28], [31], and learning at their own pace [27] are considered positive aspects of online education.

Examining the level of satisfaction of students and their continuous intention to use online learning can help to improve efficiency and eliminate its shortcomings. Finding students' preferences between two learning methods can also measure the acceptance of the current learning method. The satisfaction level is related to the responses of users about their feeling, preferences, and perceptions when using a system which is usually obtained by using questionnaires [32]. The continuance of intention to use is defined as one's intention to continually use or reuse a system [33].

In recent years, a lot of research has been done on the level of satisfaction and acceptance of online education among students, and the number of these studies has been increasing after the Covid-19 pandemic era. In most studies, students had a positive attitude and sufficient satisfaction with online education and its effects [24], [31], [34]–[43]. In [44], a high level of online self-efficacy, generalized moderate anxiety, and little fear of covid-19 caused a high level of satisfaction was shown. Stimulation and attractiveness can also be mentioned as influential factors in the level of satisfaction with online learning [45].

Some of the most important factors in the effectiveness of online learning are students' characteristics, such as demographic characteristics and digital knowledge and skills [46]. Despite most of the results, some studies show that students prefer the blended system [27], [47]–[49]. In some other research, students' preferences for face-to-face learning were found to be higher than for online learning [29], [50], [51], and findings of [52] also point to the dissatisfaction of students with online education. The research done in [53] also shows that the perceived disadvantages of online learning are more than the advantages. Regarding the continuous intention to use the online learning method, different research results are observed. The results of some research largely explained continuance intention [33], [54]. In contrast, the result of [55] showed that the majority of students did not want to continue learning by online method. Interaction between students and instructors and service quality can affect continuance intentions for online learning [56]. Also, teaching quality and time management benefits can influence students' intention to use online learning in the future [57]. To our knowledge, no previous research has examined the relationship between the level of satisfaction and continuous intention.

According to some research, the level of satisfaction with online learning can affect their academic performance [58]–[60]. Findings of studies regarding students' academic achievements in an online setting are not so uniform. Namely, some studies have shown that students perform better with online learning in their academic achievements [58], [59], [61]–[66], while other studies have shown that online learning can cause a drop in academic performance [67], [68]. Yet again, the results of [69] showed that student performance remained similar in face-to-face learning compared

to online learning. Findings of [51] conclude that there is a weak relationship between student academic achievements and perceptions.

The first case of Covid-19 disease in Turkey was announced on 10 March 2020 by the Ministry of Health of Turkey. Higher Education Board Members and university rectors made continuous and direct connections under the Presidency of the Council of Higher Education (CoHE) to initiate a transition to online education [70]. Subsequently, Eastern Mediterranean University made a sudden shift in delivering teaching-learning strategies by temporarily transitioning to online learning to meet its educational goals. To support this shift, many web-based content delivery systems (e.g., Moodle, Microsoft Teams) were used.

To our knowledge, no prior large-scale studies have examined the level of students' satisfaction and academic performance with online learning during the Covid-19 pandemic in Northern Cyprus, and the results of this research can be effective in the future decisions of educational institutions. One of the main objectives of this research is to find out students' attitudes toward and perceptions of online learning. The academic performance of students during the two years of the Covid-19 pandemic period with the online learning method and the two years before the Covid-19 pandemic period with the traditional learning method are compared together in this research. The current study tried to answer the following research questions:

What is the level of satisfaction of Eastern Mediterranean University students with online learning during the Covid-19 pandemic?

Are there significant differences regarding online learning satisfaction according to participants' IT skill level and prior online learning experiences?

What has been the impact of the redirection to online education on the academic performance of students during the Covid-19 lockdown period?

2.1.3 Methodology

Data Collection: The study was conducted from January to February 2022. A cross-sectional descriptive design was utilized to achieve research goals [71]. The data collected in this research consists of students' attitudes toward online learning and their academic performance information.

Data were collected from the participants using questionnaires. The data collection process was done through an internet-based questionnaire administrated by the Information Technologies Directorate at Eastern Mediterranean University, and the link to the online survey was shared amongst all the registered students by the official bulk email system of the university. Participants were also informed that this questionnaire was voluntary and anonymous before answering questions in the survey. To collect data, one of the most familiar methods, the 5-point Likert scale employed. This scale of measuring satisfaction had 5 answer options, including strongly agree, agree, neutral, disagree, and strongly disagree. These options allowed us to determine the level of satisfaction with the online learning system.

In order to better and more accurately examine the effectiveness of online learning on students, detailed information on their academic performance was obtained. Students' administrative academic records were obtained from the academic and student affairs of Eastern Mediterranean University without referring to the student's information to

maintain anonymity. This data includes differences between students' overall grade point average (GPA) in 2 years of face-to-face education before the Covid-19 pandemic, including four academic semesters between 2018 and 2020, and 2 years of online learning during the Covid-19 pandemic between 2020 and 2022.

Sample Size: The study population for the survey consisted of 1580 respondents, 377 did not respond, and 116 did not respond fully. A total of 1087 graduate and undergraduate students from different fields of study fully responded to the survey. The data obtained for the academic performance of the students includes the information of all undergraduate, master, and doctoral students of the Eastern Mediterranean University during the research period. All participating students were from the same university.

Instrument: The survey tool employed in this paper included five items of sociodemographic characteristics of participants, with a further 25 items split across three sections, namely online learning satisfaction (OS), students' preference between face-to-face and online education (SP), and continuance intention to use online learning (CI). The sociodemographic characteristics of participants included the age group of the participants, the level of education, faculty or school where they are studying, IT skill level, and prior online learning experience. The OS section was made up of ten items (see Table 2.1), the SP section contained ten items (see Table 2.2), and the CI section was made up of 5 items (see Table 2.3). Statements in the sections designed by the researcher are based on [56], [72], [73]. Three experts in educational technology and socio-behavioral sciences contributed to the thorough selection and evaluation of research statements to guarantee clarity, conciseness, and precision. There are three different scales used in this study to measure OS, SP, and CI in the

questionnaire. Principal component analysis (PCA) was applied to all three scales separately in line with the data obtained from the current study. As stated in [74], we adopted a factor loading criterion of 0.40 in the analysis. According to the results obtained, the factor loads of 10 items in the OS scale range between 0.88 and 0.70. The OS scale is single-factor with an appropriate variance explained value of 65.2%. Factor loadings for the ten items in the SP scale were found to be between 0.90 and 0.68 and the value of variance explained for the single-factor scale was calculated as 71.1%. The factor loads of 5 items in the CI scale are between 0.91 and 0.47. The explained variance value of the single-factor CI scale was found to be 68.9%.

Table 2.1: Students' online learning satisfaction.

Code	Statement
OS1	It was accessible from all devices
OS2	It was flexible in time and space
OS3	The Materials were presented well
OS4	Learning contents were updated
OS5	It was possible to co-working with other students
OS6	Learning resources were accessible
OS7	There was good interaction between students and instructors
OS8	The assessment submission procedure was simple and reliable
OS9	Assessments were effective
OS10	The system prepared useful and accurate educational reports

Table 2.2: Students' preference between face-to-face and online education.

Code	Statement
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SP1	Online learning is more flexible in time
SP2	Online learning is more flexible in space
SP3	Online learning resources are more accessible
SP4	Online learning has better-structured classes
SP5	Teacher-Student interaction is better in online learning
SP6	The delivery of content is better in online learning
SP7	Online learning tools provide better perception
SP8	Assessments are better in online learning
SP9	Online learning tools provide reports with more detailed and comprehensive
SP10	Online learning increase motivation and passion for learning

Table 2.3: Continuance intention to use online learning.

Code	Statement
CI1	I intend to continue using online learning as a learning content delivery method
CI2	I intend to continue using online learning for assessment
CI3	I intend to continue using online learning as an interactive communication tool between students and instructors
CI4	I intend to continue using online learning as a resource-sharing space
CI5	I intend to continue using online learning in blended mode to assist my face-to-face learning

Data Analysis: To validate and analyze the data collected from the participants, several statistical analysis techniques have been used in this study by the researcher. The collected data were processed and classified using the Statistical Package for the

Social Sciences (SPSS) Version 26 and Microsoft Excel. Cronbach's alpha technique was used to assess the reliability and internal consistency of the questionnaire sections. The data collected from the questionnaires were analyzed and presented using descriptive analysis. Skewness and kurtosis were used to determine whether the data were normally distributed in terms of the independent variables to which the analysis of the dependent variables we discussed in the study would be carried out [75]. All groups analyzed in the study were found to be normally distributed according to all dependent variables. MANOVA was used to find any differences between independent groups on dependent variables, and one-way ANOVA was used to find out statistical evidence that there is a significant difference between the means of independent groups. Also, we used the post hoc test in order to find out exactly which groups are different from each other.

2.1.4 Results

Sociodemographic Characteristics: This section provides some basic demographic data about the participants. Table 2.4 shows the responses of participants to the questions related to age group, faculty or school, level of education, IT skill level, and prior online learning experience.

Table 2.4: Sociodemographic Characteristics of Sample Respondents.

Variable	Labels	Frequency Distribution	Percentage
Age Group	18 years and below	53	4.9%
	19–29	994	91.4%
	30–39	33	3.0%
	40 years and above	7	0.7%

Faculty/School	Architecture	34	3.1%
	Art and Science	164	15.1%
	Business and Economics	88	8.1%
	Communication and Media Studies	39	3.6%
	Health Sciences (Medicine, Dentistry, Health Services, Pharmacy)	195	18%
	Education	106	9.7%
	Engineering	243	22.4%
	Law	133	12.2%
	Tourism	31	2.8%
	Computing and Technology	54	5.0%
Level of Education	Undergraduate	1010	92.9%
	Master	27	2.5%
	PhD	50	4.6%
IT Skill Level	High	478	44.0%
	Moderate	65	6.0%
	Low	544	50.0%
Prior Online Learning Experience	Yes	501	46.1%
	No	586	53.9%

According to Table 2.4, the majority of participants were in the 19–29 age group. 4.9% of participants are 18 years and below, 91.4% belong to the age group of 19–29 years, 3% are in the age group of 30–39 years, and 0.7% are in the age group of 40 years. As

revealed in Table 2.4, participants from different faculties and schools participated in this online survey. Most of the participants are from the faculty of engineering (22.4%), faculty of art and science (15.1%), health sciences (18%), and faculty of law (12.2%). The level of education of the majority of students who participated in this study is undergraduate (92.9%). 4.6% of participants are studying for Ph.D., and 2.5% are studying for a master's at university. Most participants in this study either had high IT skill levels (44%) or low levels of IT skills (50%). Also, 6% of them mentioned that they have a moderate level of IT skills. 46.1% of participants have already experienced online education, and 53.9% have experienced this type of education for the first time.

Reliability: Reliability refers to the consistency of measures on a specific instrument and should calculate before using an instrument [76]. The most widely used test to determine the internal consistency of an instrument is Cronbach's alpha [77]. This study used Cronbach's alpha method to test the reliability of each section. As shown in Table 2.5, the Cronbach Alpha coefficients for each section of the questionnaire ranged from 0.872 to 0.954. From the values of Cronbach's alpha, it can be concluded that the validity of this research for each section is very reliable. Two of them are classified as excellent ($0.940 > 0.9$, $0.9554 > 0.9$), and one of them is in good classification ($0.8 < 0.872 < 0.9$) [78].

Table 2.5: Reliability of Constructs.

Latent Variables	No. of Items	Cronbach's Alpha
Student's online learning satisfaction	10	0.940
Students' preference between face-to-face and online education	10	0.954
Continuance intention to use online learning	5	0.872

Student's Online Learning Satisfaction: As presented in Table 2.6, most of the students agreed that online learning tools used in the university (Microsoft Teams and Moodle) were accessible from all devices (83.4%), and they also agreed regarding the flexibility of online learning on time and space (67.2%). Participants confirmed that materials were presented well (69.7%), learning resources were accessible (79.2%), and learning contents were updated (76.8%). More than half of the participants agreed that there was a possibility of co working with other students (60.6%), and there was good interaction between students and instructors (64.9%). Regarding assessments, most of the students feel that assessments in online learning were effective (67.3%) and the submission procedure was easy and reliable (67%). From the students' point of view, educational reports prepared by the online system were useful and accurate (67.9%). The highest satisfaction is related to the accessibility of online learning, and the lowest is related to co working ability in online learning. In general, students who participated in this study held a high level of satisfaction with online learning ($M = 3.81$). The descriptive statistics of students' online learning satisfaction are revealed in Table 2.7.

Table 2.6: Students' online learning satisfaction.

Code	SD (1)		D (2)		N (3)		A (4)		SA (5)	
OS1	49	4.5%	51	4.7%	80	7.4%	477	43.9%	430	39.6%
OS2	71	6.5%	107	9.8%	179	16.5%	379	34.9%	351	32.3%
OS3	74	6.8%	98	9.0%	157	14.4%	362	33.3%	396	36.4%
OS4	57	5.2%	74	6.8%	121	11.1%	399	36.7%	436	40.1%
OS5	126	11.6%	141	13.0%	161	14.8%	348	32.0%	311	28.6%
OS6	65	6.0%	62	5.7%	99	9.1%	378	34.8%	483	44.4%
OS7	127	11.7%	113	10.4%	141	13.0%	343	31.6%	363	33.4%
OS8	133	12.2%	109	10.0%	117	10.8%	341	31.4%	387	35.6%
OS9	130	12.0%	98	9.0%	127	11.7%	354	32.6%	378	34.8%
OS10	94	8.6%	79	7.3%	176	16.2%	339	31.2%	399	36.7%

Table 2.7: Descriptive statistics of students' online learning satisfaction.

Code	Mean	Std. Error of Mean	Std. Deviation
OS1	4.093	0.031	1.027
OS2	3.765	0.036	1.190
OS3	3.835	0.037	1.207
OS4	3.996	0.034	1.122
OS5	3.531	0.040	1.333
OS6	4.060	0.035	1.140
OS7	3.646	0.041	1.344
OS8	3.681	0.041	1.366
OS9	3.692	0.041	1.345

OS10	3.800	0.038	1.249
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Students' Preference between Face-to-Face and Online Education: Table 2.8 shows the students' preferences for online and face-to-face learning. The majority of students agree that online learning is more flexible in time (76.9%) and space (83.8%). In addition, they agree that online learning resources are better in accessibility (78.7%). And also, most of the participants think that online learning has better-structured classes (62.8%). Teacher Student interaction has the lowest degree of superiority of online learning over face-to-face learning, with just 53.4% of the students agreeing. 64.3% of students feel that online learning tools provide better perception and 65.4% of the participants believe that delivery of content is better in online learning. Most of the students also prefer online learning over face-to-face learning in assessments (66.3%), and they believe that online learning has more detailed (68.3%) and comprehensive report tools and increases motivation and passion for learning more than face to face learning (60.1%). The participants are more interested in online learning than face-to-face and agreed regarding their preference for online learning, considering the overall mean value shown in Table 2.9 ($M = 3.76$).

Table 2.8: Students' preference between face to face and online education.

Code	SD (1)		D (2)		N (3)		A (4)		SA (5)	
SP1	70	6.4%	96	8.8%	85	7.8%	375	34.5%	461	42.4%
SP2	49	4.5%	45	4.1%	82	7.5%	408	37.5%	503	46.3%
SP3	58	5.3%	66	6.1%	107	9.8%	356	32.8%	500	46.0%
SP4	125	11.5%	115	10.6%	164	15.1%	275	25.3%	408	37.5%
SP5	182	16.7%	143	13.2%	182	16.7%	247	22.7%	333	30.6%

SP6	136	12.5%	91	8.4%	149	13.7%	306	28.2%	405	37.3%
SP7	129	11.9%	107	9.8%	152	14.0%	306	28.2%	393	36.2%
SP8	151	13.9%	93	8.6%	122	11.2%	325	29.9%	396	36.4%
SP9	106	9.8%	77	7.1%	162	14.9%	327	30.1%	415	38.2%
SP10	202	18.6%	92	8.5%	140	12.9%	285	26.2%	368	33.9%

Table 2.9: Descriptive statistics of students' preference between face-to-face and online education.

Code	Mean	Std. Error of Mean	Std. Deviation
SP1	3.976	0.036	1.198
SP2	4.169	0.032	1.040
SP3	4.080	0.034	1.130
SP4	3.668	0.042	1.370
SP5	3.374	0.044	1.455
SP6	3.693	0.042	1.370
SP7	3.669	0.041	1.362
SP8	3.664	0.042	1.399
SP9	3.799	0.039	1.286
SP10	3.483	0.045	1.488

Continuance Intention to Use Online Learning: The study intends to examine the continuous intention of students to use online learning tools. The findings listed in Table 2.10 show that most of the participants agree to continue using online learning as a learning content delivery method (73.6%), assessment tool (72.7%), and interactive communication tool between students and instructors (73.8%). The

majority of students intend to use online learning as a resource-sharing space (82.4%). And at the same time, more than half of the participants believe that they intend to continue using online learning in blended mode to assist with face-to-face learning (66.4%). Overall, they have a strong intention to continue using online learning, as figured out in Table 2.11 ($M = 3.90$).

Table 2.10: Continuance intention to use online learning.

Code	SD (1)		D (2)		N (3)		A (4)		SA (5)	
CI1	121	11.1%	73	6.7%	93	8.6%	314	28.9%	486	44.7%
CI2	126	11.6%	71	6.5%	100	9.2%	320	29.4%	470	43.2%
CI3	105	9.7%	70	6.4%	110	10.1%	347	31.9%	455	41.9%
CI4	75	6.9%	29	2.7%	87	8.0%	386	35.5%	510	46.9%
CI5	118	10.9%	99	9.1%	148	13.6%	337	31.0%	385	35.4%

Table 2.11: Descriptive statistics of continuance intention to use online learning.

Code	Mean	Std. Error of Mean	Std. Deviation
CI1	3.893	0.041	1.339
CI2	3.862	0.041	1.346
CI3	3.899	0.039	1.280
CI4	4.129	0.034	1.123
CI5	3.710	0.040	1.323

MANOVA: According to the MANOVA analyses performed, there was no significant difference between the age groups' independent variables and dependent variables ($\lambda = 0.996$, $F = 0.787$, $p = 0.580$). Education level also showed no significant difference

with dependent variables ($\lambda = 0.989$, $F = 1.880$, $p = 0.081$). Results revealed that students' IT skill levels resulted in significant differences in the dependent variables ($\lambda = 0.932$, $F = 12.503$, $p < 0.001$). The other independent variable that showed significant differences from the dependent variables is the Prior Online Learning Experience ($\lambda = 0.983$, $F = 6.193$, $p < 0.001$).

One-Way ANOVA: Based on the ANOVA analyses performed, the results regarding the significance of the effect of IT skill level and prior online learning experience independent variables on OS, SP, and CI dependent variables are presented in Table 2.12.

Table 2.12: Univariate Tests.

Independent Variable	Dependent Variable	Sum of Squares	df	Mean Square	F	p
Age Group	Total-OS	1.0958	2	0.5479	0.5857	0.557
	Total-SP	0.2040	2	0.1020	0.0886	0.915
	Total-CI	1.2387	2	0.6193	0.5982	0.550
Level of Education	Total-OS	2.8595	2	1.4298	1.5283	0.217
	Total-SP	5.1988	2	2.5994	2.2575	0.105
	Total-CI	6.4277	2	3.2138	3.1041	0.045
IT Skill Level	Total-OS	62.2891	2	31.1445	33.2916	< 0.001
	Total-SP	74.9218	2	37.4609	32.5337	<0.001
	Total-CI	52.7297	2	26.3649	25.4649	<0.001
Prior Online Learning Experience	Total-OS	13.5487	1	13.5487	14.4827	<0.001
	Total-SP	20.9846	1	20.9846	18.2245	<0.001
	Total-CI	12.5160	1	12.5160	12.0887	< 0.001

As shown in Table 2.12, among the dependent variables considered in terms of the IT skill level independent variable, OS shows a significant difference ($F = 62.28$, $p < 0.001$). The analysis also revealed a significant difference between IT skills and SP with $F = 74.92$ and $p < 0.001$ and CI with $F = 52.73$ and $p < 0.001$. In other words, in the IT skill level, students with higher or lower levels of IT skills are not likely to be equal on the dependent variables.

Similarly, an ANOVA analysis was conducted to test the difference between students' prior online learning experiences. It revealed significant differences between students with prior online learning experiences and students without prior online learning experiences for OS with $F = 13.55$ and $p < 0.001$, SP with $F = 20.98$ and $p < 0.001$, and CI with $F = 12.52$ and $p < 0.001$. In other words, all univariate ANOVAs were significant.

Level of IT Skill Post Hoc Tests: Tukey HSD, one of the Post-Hoc tests, was applied to determine the source of the difference in the IT skill level independent variable. As can be seen from Table 2.13, the OS scores of students with high IT skill levels were found to be significantly higher on average than those with low IT skill levels, and students with low IT skill levels showed significantly lower averages than students with a moderate level of IT skill.

Table 2.13: Post Hoc Comparisons—IT Skill Level.

	Comparison						
Dependent Variable	IT Skill Level	IT Skill Level	Mean Difference	SE	df	<i>t</i>	<i>p</i>

Total OS	High	Moderate	0.192	0.0607	1084	3.16	0.005
	High	Low	1.027	0.1279	1084	8.03	<0.001
	Low	Moderate	-0.836	0.1270	1084	-6.58	<0.001
Total SP	High	Moderate	0.245	0.0676	1084	3.62	<0.001
	High	Low	1.108	0.1425	1084	7.77	<0.001
	Low	Moderate	-0.863	0.1415	1084	-6.10	<0.001
Total CI	High	Moderate	0.144	0.0641	1084	2.25	0.074
	High	Low	0.951	0.1353	1084	7.03	<0.001
	Low	Moderate	-0.807	0.1343	1084	-6.01	<0.001

According to the results shown in Table 2.13, students with a high level of IT skills had a higher average SP score than students with a moderate and low level of IT skills. In addition, students with a low level of IT skills had a lower average SP score than those with a moderate level of IT skills.

The CI scores of the students with a high level of IT skills also were found to be averagely higher than those with a moderate level of IT skill level, according to Table 2.13. Also, students with a low level of IT skills had a lower average CI score than students with a moderate level of IT skills.

Prior Online Learning Experience Post Hoc Tests: Regarding the main effect of the prior online learning experience, a significant effect was found. For the OS score for the prior online learning experience, statistically significant differences were not found, as shown in Table 2.14.

Table 2.14: Post Hoc Comparisons—Prior Online Learning Experience.

	Comparison						
Dependent Variable	Prior Experience	Prior Experience	Mean Difference	SE	df	t	p
OS	Yes	No	0.180	0.101	1081	1.78	0.075
SP	Yes	No	0.359	0.066	1085	5.39	<0.001
CI	Yes	No	0.273	0.0631	1085	4.33	<0.001

We note statistically significant differences between students with experience and without experience in online learning. Students with online learning experience had significantly higher average SP scores than other students (Table 2.14).

The results also show a significantly higher average CI score for students with online learning experience than students without online learning experience (Table 2.14).

Students' Academic Performances: According to Table 2.15, changes in the GPA of undergraduate, master, and doctoral students can be seen before and during the Covid 19 pandemic. The GPA of undergraduate students was almost unchanged, with a decrease of 0.24%. The biggest change in GPA is for master students, who had a sharp

drop in their academic performance, with a 6.38% decrease. Doctoral students have also faced a 3% drop in GPA.

Table 2.15: Students' Academic Performance Changes.

Level of Study	GPA Changes
Doctorate	Decreased by 3.31%
Master	Decreased by 6.38%
Undergraduate	Decreased by 0.24%
Grand Total	Decreased by 3.64%

Academic results of students in the whole university have faced a slight drop. The GPA of students during the two years of the Covid 19 pandemic, when the education was online, faced a drop of 3.64% compared to the 2-year face-to-face period before the Covid 19 pandemic.

2.1.5 Discussion

This research tried to find the perceptions of Eastern Mediterranean University students regarding online learning. The overall mean score obtained in each section of this study indicates that students are highly satisfied with online learning and prefer to continue using it. Many aspects of online learning have the highest level of satisfaction, such as the possibility to access from all devices, up-to-date learning content, and learning resource accessibility. According to information obtained from the university, 52% of students use personal computers and 48% of mobile phones and tablets to access online learning platforms. Despite this variety in the devices used to access online learning platforms, students had the highest satisfaction with accessibility.

The results of this study show that the level of satisfaction and continuous intention can be related. Also, this study indicates that students are more interested in online learning than traditional face-to-face learning, along with a high level of satisfaction and continuous intention. The results of this research found clear support for online learning. One of the factors that can affect the perception level of participants can be fear of Covid-19 disease, which is considered effective on the satisfaction level of online learning [44]. Findings of [79] indicate that the online learning readiness of students can affect their satisfaction level. Learner-content interaction can be the other factor that can affect students' satisfaction [80].

One of the important questions that is still not discussed in the literature is the existence of a relationship between students' IT skills and their satisfaction with online learning. The analysis revealed that students with a high and medium level of IT skills had a higher level of satisfaction and continuous intention to use online learning than students with a low level of IT skills, and students with a higher level of IT skills preferred online learning to face-to-face learning more than students with a lower level of IT skills. Online learning can help students with lower levels of IT skills to improve their skills due to the reason that one of the positive aspects of online learning is creating an opportunity for students to improve their IT skills [60], [81], [82]. Therefore, online learning could be a new and different experience for students who have no previous participating experience in online learning, and therefore it can cause them dissatisfaction for the first time. But the results of this study show that not only the satisfaction of students who did not have online education experience is high, contrary to the findings of some previous studies where students preferred face-to-face learning to online learning [29], [50], [52], most of the students want to continue the

online learning and prefer it to face-to-face learning. Although, the satisfaction level of the students with previous experience with online learning was slightly higher than those who experienced online learning for the first time. The results also showed that students believed that flexibility in time, flexibility in place, and ease of access to resources were the most important reasons for preferring online to face-to-face learning. In online learning, the students can learn asynchronously at any time [83] and any place during the day, and it is possible to access, view, and download the resources easily.

According to the analysis carried out in this research, the students of Eastern Mediterranean University had a slight drop in their academic results during online learning, which shows that the academic achievements of students from online learning do not have a great impact on their level of satisfaction. These negative changes in academic performance caused by online learning can be associated with symptoms of depression and anxiety [84], and contrary to the findings of [85], digital technologies have not had a significant impact on academic achievement.

Challenges such as difficulty in communication and the use of technology, absenteeism [86], less motivation to work, and noticeably more procrastination [87] can affect students' academic performances. The findings of this research also show that master's and doctoral students have more drop in academic achievements than undergraduate students. This result is inversely proportional to many other research studies, which found that the overall academic achievement of graduate students improved in online learning [73]. Moreover, our results indicate that academic achievements and the level of satisfaction of students with online learning at Eastern Mediterranean University do not affect each other.

In this research, online learning was examined from the perspective of students, and its results can be important in terms of the number of participants. To fill one of the existing research gaps, the relationship between students' IT skills and their previous experience of using online education was also analyzed. The relationship between students' satisfaction with online learning and their academic achievement was also investigated, and unlike most previous studies, no significant relationship was found between them.

2.1.6 Conclusion

The aim of the study was to find out the perceptions of individual students at Eastern Mediterranean University about online learning during the Covid-19 pandemic period. This study showed acceptable levels of satisfaction regarding online learning. This study highlights Eastern Mediterranean University students' perceptions and attitudes, which showed online learning as a flexible and useful learning method during the Covid-19 pandemic period. Participants reported that they preferred online learning over traditional face-to-face learning. Besides, students' responses demonstrated that flexibility in time and place and ease of access to resources are the most important factors in preferring online learning over traditional learning. The participant's responses to the online survey conducted in this study showed that the majority want to continue using online learning. Students' level of satisfaction is not affected by their academic performance, and findings indicate a slight drop in their academic achievements. A practical implication of the mentioned findings is that the assessment methods should be improved to get better results from the academic achievements of students. There is also a practical implication related to IT skills, in that the university should try to teach computer skills to students. This is the first study exploring the perceptions, attitudes, and academic performance of students during the Covid-19

pandemic at Eastern Mediterranean University. One of the strong points of this study is considered to be its large sample size in which 1087 students participated. Finally, it should be noted that this research should be done on the perception and attitudes of instructors toward online learning at Eastern Mediterranean University in the future. Examining the relationship between the results of students' and instructors' satisfaction levels with online learning can also be useful. Another critical challenge that we need to study in the future is to examine the relationship between the digital divide and the level of student satisfaction with online learning. Future research should also consider the effects of other variables, such as the learning style of students and the teaching style of instructors, on students' level of satisfaction and academic achievements [88].

2.2 A Look at Students' Academic Achievements and Satisfaction Level with Online Learning Evaluations

Online learning has become a popular and convenient option for students seeking to further their education. However, the assessment process in online learning environments can be a source of frustration for students [89]. While traditional in-person courses often rely on exams and quizzes to evaluate student learning, online courses may also utilize online quizzes, projects, and other types of assessments [90].

One of the key factors that can impact student satisfaction with online learning is the assessment process. In a traditional in-person course, students may be used to taking exams and quizzes in a face-to-face setting, with the opportunity to ask questions and receive immediate feedback. In an online course, however, assessments may be conducted entirely online, which can be less personal and more impersonal for students. In addition, online assessments may be more vulnerable to technical issues,

such as internet connectivity issues or problems with submitting assignments. All of these factors can contribute to lower levels of student satisfaction with online learning assessments.

Studies have shown that student satisfaction with online assessments can be influenced by a number of factors. One such factor is the perceived fairness of the assessment. Students may be more satisfied with online assessments if they feel that the assessments are fair and unbiased. This may include ensuring that all students have equal access to the necessary technology and resources, as well as providing clear and detailed instructions for completing assessments[89].

Another factor that can impact student satisfaction with online assessments is the level of support and feedback provided. Students may be more satisfied with online assessments if they receive timely and helpful feedback on their performance. This can include feedback on both the content of their work and the overall quality of their submissions.

Additionally, the level of interaction and engagement in online assessments can also impact student satisfaction. Studies have shown that students may be more satisfied with online assessments that allow for more interaction and engagement, such as through the use of interactive quizzes [90] or peer review [89].

Overall, it is clear that student satisfaction with online assessments is influenced by a range of factors. By understanding these factors and working to address them, educators can work to create more effective and engaging assessment experiences for online learners.

In recent years, there has been a growing body of research examining the impact of online learning on student academic achievements. Findings from the research on online learning and academic achievement have been mixed. Some studies have found that students who participate in online learning may experience similar or even higher levels of academic achievement compared to their counterparts in traditional in-person learning environments [91]. Other research has found no significant difference in academic achievement between online and face-to-face learning [92]. One potential reason for the mixed findings is that the relationship between online learning and academic achievement is not always straightforward. Factors such as student motivation, prior knowledge and experience, and access to technology and other resources can all impact academic achievement in online learning environments [93]. For example, students who are highly motivated and have strong prior knowledge may be more likely to excel in online learning environments. On the other hand, students who are less motivated or who lack access to necessary technology and resources may struggle to achieve the same level of academic success in online learning.

In addition, the design and delivery of the online course can also impact academic achievement [94]. Courses that are well-designed and delivered, with clear learning objectives and effective assessment strategies, may lead to higher levels of academic achievement for students. Online courses that are poorly designed or delivered, on the other hand, may lead to lower levels of academic achievement.

2.3 A Review of Multi-objective Optimization

An introduction to the fundamentals of optimization, multi-objective optimization, and the multi-objective evolutionary algorithm is presented in this section.

2.3.1 Optimization

Humans are always looking for better solutions, which is an indicator of the basic drivers in human cultural evolution, and they always try to improve, but they ignore what level they reached in the past. The formal form of these searches for the best possible solutions in mathematics or engineering is known as optimization. When engineers start designing a structure or a complex system, the goal is definitely to achieve an optimal design. When you think an object or a process can be made better, you are actually thinking about optimization. Optimization involves selecting the "best" solution from a set of possible solutions, and the degree of goodness of the solution is quantified by minimizing or maximizing an objective function (eg, cost) [95] The main goal of optimization is the effective and practical use of available resources. From a mathematical point of view, optimization of a problem means finding the best possible solution concerning an objective function, which is used to evaluate the solutions to find the best one.

2.3.2 Mathematical Definition

In most optimization problems, there is a single goal to solve (or objective function), which optimization objective can be to maximize or minimize the value of a function by applying many restrictions in the form of equality and inequality expressions [96]. Generally, optimization problems have the following mathematical form:

$$\text{Minimize } f(x) \quad (2.1)$$

$$\text{Subject to } g_i(x) = 0 \quad i = 1, \dots, p \quad (2.2)$$

$$h_j(x) \geq 0 \quad j = 1, \dots, q \quad (2.3)$$

$$x \in \chi \quad (2.4)$$

Here x is referred to as a set of decision or optimization variables. The decision variables consisting of independent variables are selected to find the optimal solution, and the vector x containing n decision variables can be shown as $x = (x_1, \dots, x_n)^T$.

Constraints represent any restrictions on the values of the decision variables and any optimization formula must be complete and not leave out any constraint. Regardless of the solution, the constraint must be satisfied. The constraint may be determined in the form of equality constraints (Eq. 2.2) or inequality constraints (Eq. 2.3) and their values determine the feasibility of the solutions.

Sometimes we find that most problems have multiple objectives and using single-objective optimization is insufficient, so we have to use multi-objective optimization.

2.3.3 Applications

Today, mathematical optimization algorithms are essential in our daily life and we use them in different aspects of life to find the best solution for any problem. Some of the most important real-world optimization applications are as follows:

- Agriculture: optimization of energy consumption and environmental impacts of chickpea production [97], path planning of an agricultural mobile robot [98], and agricultural land classification and evaluation [99].
- Architecture: optimization of form and facade of an office building [100] and optimization of architectural shape [101].
- Aviation: flight trajectories optimization [102] and optimization of hypersonic aircraft [103].
- Chemistry: generate highly-accurate semi-empirical potential energy surfaces [104], prediction of chemical patterns [105], and prediction of structures of nanoparticles [106].
- Education: educational timetabling problems [107], test data generation [108], exam paper generation [109], and question-answering systems [110].

- Engineering: designing hydraulic presser to maximize the nominal pressure rating and fully loaded power while minimizing the oil injection volume [123], supply chain management [111], production planning and detailed scheduling [112], and optimization of cable-stayed bridges [113].
- Medical: disease diagnosis [114], cancer detection and prediction [115], radiotherapy treatment planning, and RNA design and structure prediction [116].

The common denominator of all these problems is due to a large number of alternative solutions in the framework of the search algorithm that can support human decision-makers in solving problems.

2.3.4 Multi-objective Optimization

Some optimization problems require the optimization of multiple and conflicting objectives, and they are referred to as multi-objective optimization (MOO), which is challenging despite their high importance. These MOO applications can be used in engineering, computer science, sociology, economics, agriculture, medicine, etc. A multi-objective optimization problem (MOOP) is an optimization problem that involves more than one objective function that is to be minimized or maximized and the answer is a set of solutions that define the best tradeoff between competing objectives [117]. We can handle MOOP by optimizing functions $f_1(x), \dots, f_m(x)$ simultaneously, where the number of objectives can indicate by m ($m \geq 2$). Multiple-objective optimization usually has conflicting objective functions that produce a set of optimal solutions known as Pareto-optimal solutions instead of one optimal solution, since no solution can be considered to be better than any other concerning all objectives.

2.3.5 Multi-objective Optimization Methods

Multi-objective optimization methods are a class of algorithms and techniques used to solve optimization problems that involve multiple, conflicting objectives. These methods aim to find a set of solutions that trade-off the conflicting objectives in a way that is acceptable to the decision maker [118].

There are several types of multi-objective optimization methods, including scalarization methods and pareto methods.

Scalarization methods: Scalarization methods involve converting multiple objectives into a single objective function by combining them using a scalarization function. This function assigns a weight or importance to each objective, and the combined objective function is the sum of the individual objectives, each scaled by their corresponding weight. Scalarization methods can be further classified into two main categories: linear scalarization methods and nonlinear scalarization methods. Linear scalarization methods use linear combinations of the objectives, while nonlinear scalarization methods use nonlinear combinations [119].

Pareto methods: Pareto methods are a type of optimization technique that is used to solve problems with multiple conflicting objectives. These methods are based on the concept of Pareto optimality, which refers to a state in which it is not possible to improve one objective without degrading another. In other words, a Pareto optimal solution represents the best trade-off between the objectives [120].

One of the key elements in the design and implementation of computer-based problem-solving systems is the use of computational models of evolutionary processes called

evolutionary computations. Various computational evolutionary models have been proposed and studied, which we refer to as evolutionary algorithms [121]. The term Evolutionary Algorithm (EA) stands for a class of stochastic optimization methods that simulate the mechanisms of the biological evolution process and has been applied to a wide variety of problems. In EA, natural selection is simulated by a stochastic selection process. EA seem particularly desirable for solving MOO problems because they deal with a set of possible solutions simultaneously [122]. Nowadays, the multi-objective evolutionary algorithm (MOEA) has become the main approach for solving MOO problems. EA mimics common evolutionary processes such as natural selection and variation (mutation, crossover) in nature.

An EA contains four main overall steps including initialization, selection, genetic operators, and termination. Chromosomes representing candidate solutions. In the initialization step, a set of solutions called population is usually created randomly. After creating a population in the initialization step, the population members must now be evaluated based on a fitness function. The fitness function is defined to measure the fitness of each solution (individual chromosome) to determine which will reproduce and survive into the next generation according to objectives. The third step, which is genetic operators, usually includes crossover and mutation sub-steps. After selecting the best members according to the fitness function, these members are now used to create the next generation in the algorithm and new children are created according to the characteristics of the selected parents. In each generation, new solutions (offspring) are created by genetic operators. The crossover operation is performed to recombine parts of these parents to create child solutions, and with the mutation operation, a small change is made in the child solutions. From among all parents and children (solutions),

a new set called the new generation that contains better solutions is selected, which is called survivor selection. This process is repeated until finding better and more optimal solutions (evolution). Finally, in the termination step, the algorithm ends by reaching the maximum execution time or the performance threshold and the final solution is selected. When dealing with multiple conflicting objectives, unlike single-objective optimization, the EA ranking mechanism needs to be designed because there is ambiguity in whether one solution is better than another.

Multi-objective optimization methods are widely used in various fields, such as engineering, finance, and operations research. These methods can be applied to a wide range of problems, including resource allocation, scheduling, design optimization, and risk management.

2.3.5.1 Multi-objective Genetic Algorithm

MOGA is a multi-objective optimization algorithm that is based on the principle of natural selection and uses a genetic representation of solutions. MOGA generates a population of potential solutions and iteratively improves them through a process of selection, reproduction, and mutation. The solutions that are selected for reproduction are the ones that are most fit according to some fitness function, which is a measure of how well the solution performs on the objectives. MOGA uses a ranking-based selection mechanism to select the solutions that will be reproduced, and it assigns a rank to each solution based on its performance on the objectives. MOGA is a powerful optimization algorithm that can handle complex multi-objective optimization problems, but it can be computationally expensive and may require a lot of time to converge to a satisfactory solution [123].

2.3.5.2 Non-dominated Sorting Genetic Algorithm II

NSGA II is a popular evolutionary algorithm for solving multi objective optimization problems. It is an improvement over the original NSGA algorithm and is more efficient and effective in handling complex problems. NSGA II uses a ranking based approach to select the solutions that will be reproduced, and it assigns a rank to each solution based on its performance on the objectives. The rank reflects the number of other solutions that dominate the solution, and solutions with lower ranks are more likely to be selected for reproduction. NSGA II is widely used in various fields, such as engineering, finance, and operations research, and it has been shown to be effective in handling complex multi objective optimization problems [124]

2.3.5.3 S-Metric Selection Evolutionary Multi Objective Optimization Algorithm

SMS EMOA is a MOEA that uses a different approach to solve multi objective optimization problems. It works by generating a set of "reference points" in the objective space and selecting a subset of these points as the starting population. The algorithm then applies a selection operator to choose the most promising solutions and applies genetic operators to these solutions in order to generate new ones. The algorithm also uses an "S metric" to measure the distance between solutions and the reference points, and it uses this metric to guide the search toward promising areas of the objective space [125].

2.3.5.4 Adaptive Geometry Estimation based Multi- Objective Evolutionary Algorithm

AGE MOEA uses the same basic structure as NSGA II, but with a changed crowding distance calculation. It first sorts the non dominated solutions using non dominated sorting, then uses the first sorted set to normalize the objective space and estimate the Pareto front shape. It then determines the "p" value of a Minkowski p norm based on

the closest solution in the middle of the first set, and uses that p-norm to determine a survival score that balances the distance from neighboring solutions and proximity to the ideal solution. The algorithm first sorts the non-dominated solutions, and then uses the first sorted set to estimate the Pareto front geometry and calculate a survival score for each solution. The survival score takes into account both the proximity of each solution to its neighbors and its distance from the ideal solution. This allows AGE-MOEA to balance diversity and convergence in the search for Pareto optimal solutions, resulting in improved performance compared to traditional NSGA-II in various test problems [126].

2.3.6 Applications of Multi-Objective Optimization in Education

Multi-objective optimization can be a useful tool for education institutions to make more informed decisions and allocate resources effectively to achieve multiple objectives. Multi-objective optimization can be applied in various ways in the education sector. Here are a few examples:

Curriculum design: In education, curriculum design involves choosing the topics and content that should be included in a course or program. Multi-objective optimization can be used to determine the optimal curriculum that balances various objectives, such as maximizing student learning, minimizing the time required to complete the course, and minimizing the cost of the course.

Resource allocation: Education institutions often have limited resources, such as time, money, and staff, which need to be allocated effectively. Multi-objective optimization can be used to determine the optimal allocation of these resources to achieve multiple objectives, such as maximizing student satisfaction, minimizing costs, and maximizing the quality of education.

Scheduling: In education, scheduling involves creating a timetable for classes, exams, and other activities. Multi-objective optimization can be used to determine the optimal schedule that balances various objectives, such as minimizing conflicts between classes, maximizing the utilization of resources, and minimizing the time required to complete the program [127], [128].

Student placement: In education, student placement involves assigning students to different courses or programs based on their interests and abilities. Multi-objective optimization can be used to determine the optimal placement of students that balances various objectives, such as maximizing student satisfaction, minimizing conflicts between courses, and maximizing the quality of education.

Student assignment: In education, student assignment refers to the process of assigning students to different groups or teams for various activities, such as group projects or team-based learning. Multi-objective optimization can be used to determine the optimal assignment of students to groups that balance various objectives, such as maximizing the diversity of perspectives and skills within each group, minimizing conflicts between students, and maximizing the overall quality of the learning experience.

Student loan optimization: Many students rely on loans to finance their education, and the repayment of these loans can have a significant impact on their financial well-being. Multi-objective optimization can be used to determine the optimal repayment plan for student loans that balances various objectives, such as minimizing the overall cost of the loans, maximizing the flexibility of the repayment plan, and minimizing the risk of default.

Chapter 3

SYSTEM STUDY AND REQUIREMENT ANALYSIS

3.1 The Concept of Question Bank System Architecture

A question bank system is a type of computerized system that is designed to store and manage a large collection of questions, along with associated answers and other relevant information. The goal of a question bank system is to allow users to quickly and easily access a wide range of questions on a variety of different topics, and to customize their experience by selecting the types of questions that are most relevant to their needs.

The concept of our proposed system is based on the idea that different individuals have different learning styles, preferences, and needs, and that a one-size-fits-all approach to learning is not effective for everyone. By tailoring the questions to the individual's specific learning needs and preferences, the system can provide a more engaging and effective learning experience.

The architecture of our proposed question bank system typically consists of several different components, including a database to store the questions and related information, a user interface for accessing and navigating the system, and a set of algorithms and processes for recommending and personalizing the questions that are presented to users.

One key feature of the proposed system is the ability to tailor the questions that are presented to each individual user based on their interests, knowledge level, and other factors. Another important aspect of the architecture of the proposed system is the ability to allow users to create and add their own questions to the system. This can be done through a simple interface that allows users to enter new questions and answers, along with any additional information that may be relevant.

3.2 System Design and Development

The system was developed using the traditional system development life cycle (SDLC) approach. This method involves creating a fixed structure, representation, and mechanism that can be used by regular users to understand the system. It helps to provide a comprehensive overview of the various phases of the development process. In other words, SDLC is a way of building a system that is easy for users to understand and use by breaking the development process down into distinct phases and creating a clear structure for each phase [129].

The SDLC approach consists of several distinct phases, including (Figure 3.1):

Planning: In this phase, the overall goals and objectives of the system are defined, and a high-level plan for the development process is created. This may involve identifying the specific types of questions that the system will need to support, determining the target user group, and defining any other requirements or constraints.

Analysis: In this phase, the system requirements are analyzed in greater detail, and a more detailed plan for the development process is created. This may involve conducting user research to better understand the needs and preferences of the target audience, and creating detailed specifications for the system.

Design: In this phase, the overall architecture and design of the proposed system is developed. This may involve creating detailed design documents, creating mock-ups or prototypes of the user interface, and developing algorithms and processes for personalizing the questions that are presented to users.

Implementation: In this phase, the actual code for the proposed system is written and the system is built. This may involve writing the code for the database, user interface, and any other components of the system.

Testing: In this phase, the proposed system is thoroughly tested to ensure that it is reliable, efficient, and user-friendly. This may involve conducting both automated and manual testing to identify and fix any defects or issues.

Deployment: In this phase, the proposed system is released and made available to users. This may involve installing the system on servers or in the cloud, and configuring any necessary infrastructure to support it.

Maintenance: In this phase, the proposed system is continuously monitored and updated to ensure that it continues to meet the needs of users and to fix any defects or issues that may arise.

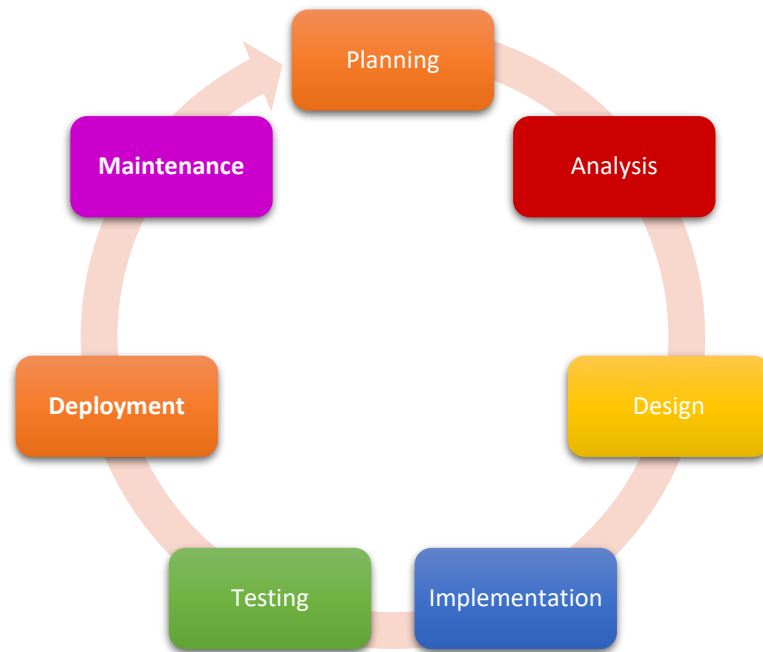


Figure 3.1: System development life cycle (SDLC)

3.3 System Actors

System actors are the entities or individuals that interact with a system in some way. In the case of our proposed question bank system, the proposed system has six types of actors that play the role of operating the system. They are listed as follows (Figure 3.2):

End users: These are the individuals who will use the system to create and manage their own question bank, as well as create quizzes.

Administrators: These are individuals who have special privileges and permissions within the system, such as the ability to manage users, create and edit questions, and view analytics and reports.

Developers: These are individuals responsible for developing and maintaining the system.

Testers: These are individuals who test the system to ensure that it is functioning correctly and meeting the required specifications.

Support staff: These are individuals who provide technical support and assistance to users of the system.

External systems: These are other systems or tools that may integrate with or interface with the question bank system, such as learning management systems, chat-bots or assessment platforms.

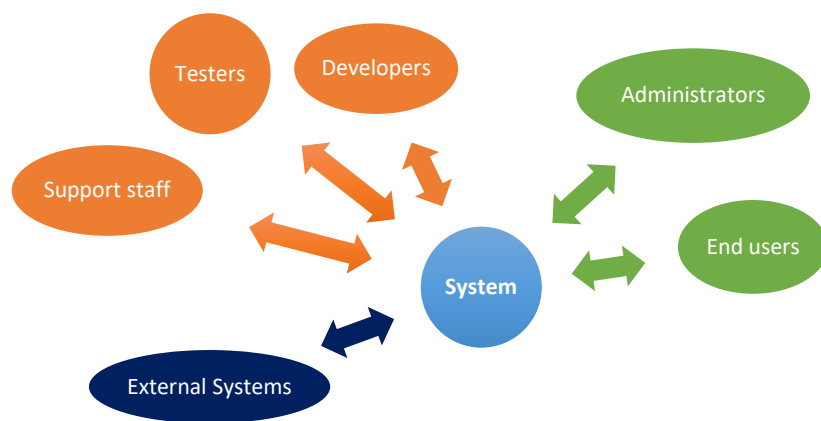


Figure 3.2. System actors

3.4 Modeling System Requirements

This section will provide a comprehensive description of the system, including both functional and non-functional requirements. It will include all necessary features to ensure that the system is fully functional and meets all requirements (Table 3.1).

The functional specifications document outlines the features and behaviors that the system must have to meet the requirements and expectations of the client, as determined through interviews and analysis of their needs. It lists the specific features

that must be included in the system in order to be considered complete and fully functional. In addition to these functional requirements, the system must also possess certain non-functional features in order to operate as intended. These non-functional requirements include properties such as safety, reliability, efficiency, and portability. The implementation plan for these non-functional requirements is typically outlined in the system architecture, as they are integral to the overall architecture of the system.

Table 3.1: Functional and non -functional requirements of the system

Req. Type	Description	Type
Non-functional	The system should be Cross-platform compatible.	Compatibility
	The system should be able to handle a large number of users and questions without experiencing delays or downtime.	Performance
	The system should be able to handle an increase in the number of users or questions without requiring significant additional resources.	Scalability
	The system should protect user data and prevent unauthorized access to the question bank.	Security
	The system should be easy to use and navigate, with a user-friendly interface.	User experience
	The system should be easy to maintain and update over time.	Maintainability
	The system should be reliable and consistently perform as expected.	Reliability
	The system should allow users to add or remove questions, organize them into categories or tags, and set preferences for how they are displayed.	Customizability
	The system should be able to integrate with other systems or tools, such as learning management systems or assessment platforms.	Integration
	The system should have a reliable data backup and recovery system in place to prevent data loss in the event of a system failure or disaster.	Data backup and recovery
Functional	The system should allow institutes to register instructors and students to the system.	User Registration

	The system should allow instructors and students to log in to access the question bank.	User login
	The system should allow users to create, edit, and delete questions, and organize them into categories by their access level.	Question management
	The system should allow users to search for and filter questions by keywords, categories, tags, or other criteria.	Search and filter
	The system should allow users to create quizzes or assessments using their own questions or a selection of questions from the question bank by choosing the number of questions, difficulty level, and total duration for the question set.	Assessment generation
	The system should be able to adapt the difficulty of the assessment in real-time based on the student's performance obtained from external learning management systems.	Personalized Assessments
	The system should provide users with detailed reports and analytics on their question performance, including scores, time spent, and areas of strength and weakness by their access level.	Reporting and analytics
	The system should allow users to provide feedback and ratings on questions, to help improve the quality and relevance of the question bank.	Question feedback and rating
	The system should allow admin users to define different access levels for each user.	Access control

3.5 Application Architecture

Application architecture is the structure of an application, including the components that make up the application, the relationships between those components, and the patterns and principles that guide the design and evolution of the application. It is a high-level view of an application that defines how the various pieces of the application fit together and interact with each other to achieve the desired functionality. The application architecture design in figure 3.3 illustrates the graphical representation of the proposed system.

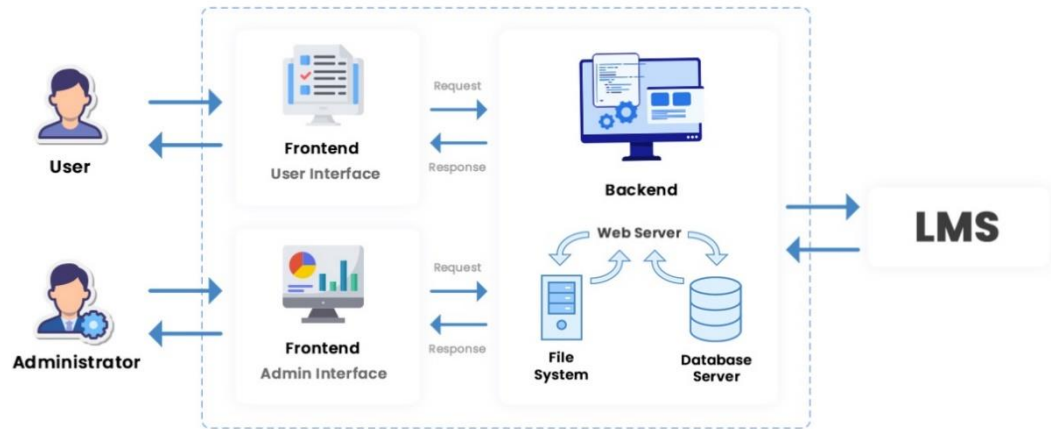


Figure 3.3: Application architecture

3.6 Database Design

Database design is the process of creating a structured plan for a database that outlines how the database will be organized and used. It involves determining what data needs to be stored in the database, what relationships exist between different data elements, and how the data will be organized to support the needs of the application or system that will be using the database.

Database architecture for our proposed system involve storing a collection of questions with unique identifiers and metadata such as subject and difficulty level, as well as information about users and their preferences. The system track which questions each user has answered correctly and incorrectly, and also store additional data such as the time spent on each. The database also includes tables for managing question sets and storing information about subjects and topics, and include additional tables for storing relevant metadata.

Question Type table: The question types table stores information about the different types of questions that are available in the question bank. It is typically used to classify

questions based on their format or other characteristics, such as multiple-choice, true/false, or fill-in-the-blank.

- Question Type ID: A unique identifier for the question type
- Type name: The name of the question type (e.g. "Multiple-choice", "True/false", "Descriptive", etc.)
- Description: A brief description of the question type.

Questions table: Stores the questions that are available in the question bank, along with their metadata such as subject and difficulty level.

- Question ID: Unique identifier for the question
- Question Type ID: The type of question (eg. Multiple-choice, Descriptive, etc.)
- Subject ID: ID belongs to the subject area of the question
- Difficulty level: Difficulty of the question
- Accessibility: Whether the question is publically accessible or private
- Duration: Time need to spent to solve the question
- Question text: The text of the question
- Correct answer: The correct answer to the question
- Source: Source of the question.

Option table: Choices table stores the possible answer choices for questions in the question bank. It is typically used in conjunction with a questions table that stores the questions themselves and an answers table that stores the user answers.

- Option ID: A unique identifier for the answer option

- Question ID: The unique identifier for the question that the answer option belongs to.
- Option label: The text of the answer option (e.g. "A", "B", "C", etc.)
- Option text: The text of the answer option.

Access Level table: The access level table stores information about the different levels of access that users of a system may have. Access levels are used to control which users can perform certain actions or access certain resources within the system.

- Access Level ID: A unique identifier for the access level
- Level name: The name of the access level
- Description: A brief description of the access level
- Permissions: A list of the actions or resources that users with this access level are allowed to perform or access (e.g. "create questions", "delete questions", "create users", "delete users", etc.).

Users table: Stores information about the users of the system, including their personal details and preferences.

- User ID: Unique identifier for the user
- Name: Name of the user
- Username: Unique username of the user
- Email: Email address of the user
- Access Level ID: Access level id of the user

- Preferences: Any preferences or settings that the user has specified (e.g. preferred difficulty level, subjects of interest, etc.)

Question history table: Stores a record of each question that a user has answered, along with the result (correct or incorrect) and any additional data such as time spent and confidence level.

- History ID: Unique identifier for the answered question log
- User ID: Unique identifier for the user
- Question ID: Unique identifier for the question
- Answer: Answer of the user to the question
- Result: Result for answer of the user to the question
- Time spent: Amount of time that the user spent on the question
- Answer Time: Date and time when answering the question.

Subjects table: Stores information about the subjects covered by the questions in the question bank

- Subject ID: Unique identifier for the subject
- Subject name: Name of the subject.

Topics table: Stores information about the topics within each subject that the questions are related to.

- Topic ID: Unique identifier for the topic
- Subject ID: Unique identifier for the subject that the topic belongs to

- Topic name: Name of the topic.

Question feedback table: Stores feedback provided by users about specific questions.

- Feedback ID: Unique identifier for the feedback
- Question ID: Unique identifier for the question that the feedback belongs to
- User ID: Unique identifier for the user
- Feedback text: Textual feedback provided by the user about the question
- Other media: Any additional media (e.g. images, videos) that may be relevant to the feedback.

Assessment table: Assessment table stores information about the assessments that have been generated by the users. An assessment is a set of questions that has been customized for a particular user based on their preferences.

- Assessment ID: A unique identifier for the assessment
- User ID: The unique identifier for the user that generated the assessment
- Title: Title of the assessment
- Questions: A list of question IDs that belong to the assessment
- Date generated: The date and time at which the assessment was generated
- Score: The score belongs to the assessment
- Duration: The total duration of the assessment
- Difficulty level: The difficulty level of the assessment defined by the user.

An entity-relationship (E-R) diagram is a graphical representation of the relationships between different entities in a database or information system. It is used to model the

structure of a database and to show how different entities are related to each other. An E-R diagram typically consists of three types of elements: entities, attributes, and relationships. Figure 3.4 shows the E-R diagram of the proposed system.

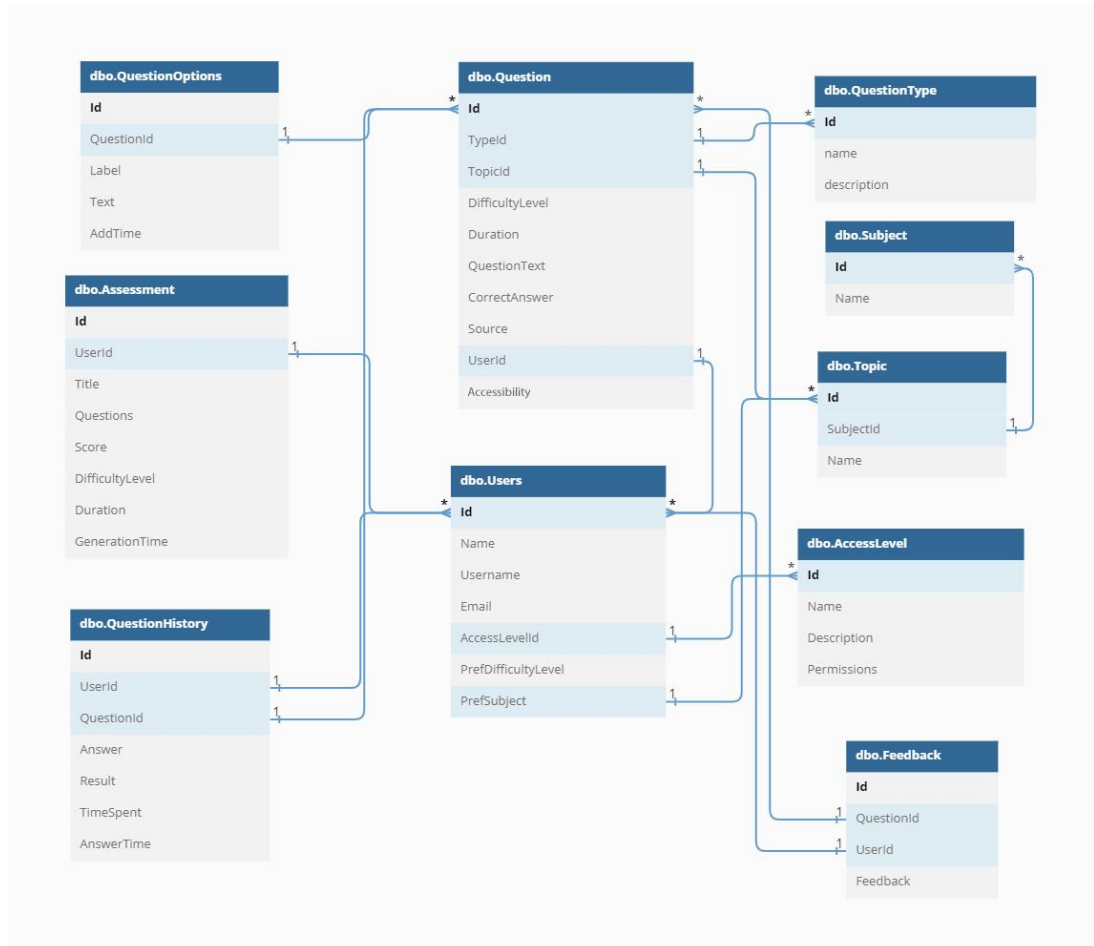


Figure 3.4: E-R diagram for the system

3.7 Data Collection

In the proposed system, data collection is carried out by adding questions through user input or importing from learning management systems (LMS) such as Moodle. This data may be structured or unstructured. The collected data is then used to create assessments for users, based on their individual needs or preferences.

3.8 Application of Modified NSGA-II Algorithm

3.8.1 Introduction

One of the most important, sensitive, and necessary parts for success and guaranteeing the efficiency of an education system is the quality of assessments. A better implementation of assessments is important in terms of making sure that students work correctly and succeed in acquiring the required knowledge. Assessment monitors the educational process of students and can also measure the quality of education provided. However, contradictory results have been observed among many students. Some students believe that assessments can be ignored in the learning process [130].

One of the tools that can help improve assessments is Question Banks. A question bank is a pool of questions that are stored to be used in assessments over time. Questions can be added over time by instructors or students. Instructors normally add questions into question banks to reuse in multiple assessments. Additionally, students can import their questions and research shows that question banks generated by students have improved students' exam performance [131]. Question banks are good potential for creating and reusing assessments in a flexible, customized, unique, and tailored formative and summative way [132]. Each question can have different features. These features can be the level of difficulty, the time required to answer, or the subject to which the question belongs. One of the methods to find the difficulty level of questions is the item analysis process which examines student responses to individual test items (questions) [133]. Another way of determining the difficulty level of questions is to ask the question designer. The answering duration can be considered the average time of previous responses or determined by the question designer. One of

the advantages of using the question bank in preparing assessments is saving time [134].

Advancement in technology has provided the opportunity for educational systems to improve their educational quality and one of the affected parts is the assessments. New technologies have given the opportunity to the educational system to conduct online exams or to evaluate students repeatedly with flexibility in place and time [135]. The questions used in these online assessments can be selected from the question bank. A set of questions can be selected randomly or purposefully.

The best solution to this selection can be found through the optimization process [119]. Selection of the best and optimal set of questions from the question bank by considering some parameters such as the difficulty level of the questions or the duration of assessment can be a multi-objective optimization (MOO) problem. The problem of subset selection is to select a subset from a whole set to accomplish specific objectives [136]. The MOO problems involve two or more optimization objective functions [137]. In the problem of choosing questions from the question bank, the objectives can be difficulty level and duration.

The MOO methods are useful to solve the problem of selecting questions from the question bank. The commonly used method of MOO are as follows:

Random Selection: In this method, the solutions are chosen randomly. In the application of the random selection method on the question selection problem, the algorithm starts with selecting the first question from the question bank based on constraints and then conditions of objective functions are checked and in the case of

not fulfilling the conditions, another question is selected. This process continues until a sufficient number of questions that meet user requirements are selected. Another way of using random selection is to search for all the questions considering constraints from the question bank and randomly select a number of them. In [138], the application of a randomized algorithm to generate a question paper can be found.

Multi-objective particle swarm optimization (MOPSO): The particle Swarm Optimization (PSO) algorithm is famous and attractive because of its simplicity and effectiveness in finding a solution for single and multi-objective optimization problems. In [139], one of the first use of PSO to solve multi-objective problems was done using MOPSO. The implemented algorithm uses the Pareto dominance to search for solutions to multi-objective problems and uses the second population or exterior archive to save non-dominated solutions and helps in finding of next generations [140]. The Question selection problem is implemented by using a modified method of PSO in [141] and [4].

Multi-objective Ant Colony Optimization (MOACO): The main thought behind Ant Colony Optimization (ACO) is to solve the problem in order to search for a minimum cost path in a graph, and use artificial ants to search for good paths. This process is inspired by the foraging behavior of real ants for seeking a path between their colony and source of food [142]. In recent years, many papers have been published introducing ACO algorithms for multi-objective problems. In [143], an ACO algorithm was implemented for the optimization problem of choosing questions from the question bank.

MOGA: Genetic algorithm (GA) is a type of self-adaptive global search optimization algorithm which imitates Charles Darwin's theory of the natural evolution of living beings [144]. The multi-objective implementation of GA called MOGA was introduced for the first time in 1993 and used the non-dominated classification of a GA population. The MOGA clearly emphasizes non-dominated solutions and maintains diversity among non-dominated solutions at the same time [123]. The majority of prior research has applied GA and MOGA to solve the optimization problem of selecting questions from the question bank. Many different improved GA implemented in [145],[146],[147],[148],[149], and [150] to find solutions for the optimization problem of selecting questions for a test paper from the question bank.

AGE-MOEA: The AGE-MOEA method was recently proposed in the field of MOO to better achieve the set of all Pareto efficient solutions (Pareto front) by using an adaptive evolutionary algorithm based on non-Euclidean geometry. Based on this, it estimates the geometry of the generated front and adapts the diversity and proximity metrics accordingly [126]. According to the investigations we have done, it was found that no study has been done on using AGE-MOEA to solve the optimization problem of question selection from the question bank.

SMS-EMOA: SMS-EMOA uses a combination of non-dominated sorting and hypervolume indicator-based selection and it works perfectly in searching for the perfect distributed solution set to estimate the Pareto front [125]. To our knowledge, no prior studies have been done on using SMS-EMOA to solve the optimization problem of question selection from the question bank.

NSGA-II: An elitist non-dominated sorting GA (NSGA- II) developed in 2000 which uses elitist, diversity-preserving mechanisms and emphasis on non-dominated solutions [124]. NSGA-II has become a popular method for solving MOO problems. As far as we know, there is no previous research regarding solving the problem of question selection from question banks using NSGA-II.

Hybrid Methods: A hybrid algorithm is a combination of multi algorithms that are developed to perform better than the individual algorithms to solve the same problem by selecting one or changing between them during the execution of the algorithm [151]. Hybrid algorithms also perform well in solving MOO problems. In [152], a combination of an improved adaptive GA with particle swarm optimization was used to find solutions for choosing questions for test papers from the question bank. A test paper generation system is implemented based on Ant Colony Hybrid GA in [153]. The implemented method in [154] and [155] introduces the simulated annealing algorithm to optimize the problem of question selection for use in test papers based on GA.

Most of the previous studies were limited to a question bank containing a small number of questions or the collected data was not real. In the mentioned studies, many important multi-objective evolutionary algorithms have no implementation and are not examined.

In this study, we propose an efficient MOO approach for the problem of selecting questions from a question bank that can be used in the generation of exam papers or intelligent learning assistant systems. The proposed approach is based on the NSGA-II method for MOO. Also to fill mentioned literature gaps, this paper examined many

important multi-objective evolutionary algorithms including MOGA (as a base algorithm for most of the studies), AGE-MOEA, SMS-EMOA, and NSGA-II on the optimization problem and compared the results for each of them.

This study seeks to examine the efficiency of our proposed method for finding a solution for the optimization problem of selecting questions from the question bank by considering the results obtained for the execution time, objective function value, and the number of generations to reach the final solution. This study also aims to explore the effect of the weight coefficient for two objective functions on the solution of the optimization problem.

3.8.2 Methodology

This paper researches the MOO problem for extracting questions from the question bank. We define question bank with m questions as $Q = \{Q_1, Q_2, \dots, Q_m\}$, in which each question Q_i has different parameters. Each question can represent as $Q_i = \{U_i, D_i, T_i\}$, where U_i is question unique code, D_i is questions' level of difficulty and T_i is the time allotted to answer the question. The time allotted to answer the question is determined by the question designer, and the difficulty level of each question is dynamically calculated by [156]:

$$D_i = \frac{CA_i}{TA_i}, D_i \in [0,1], i \in \{0,1, \dots, m\} \quad (3.1)$$

Where CA_i is the number of correct answers and TA_i is the total number of answers to the question.

The difficulty level of the questions in the question bank (D) and the time allotted to answer the question (T) are shown as follows:

$$D = \begin{bmatrix} D_1 \\ D_2 \\ \vdots \\ D_m \end{bmatrix}, T = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_m \end{bmatrix} \quad (3.2)$$

Each set of selected questions is a 1 in m matrix, where each S_j indicates the status of the question Q_i of question bank in the selected set:

$$S = [S_1, S_2, \dots, S_m] \text{ where } S_j = \begin{cases} 1 & \text{if } Q_j \text{ in selected set} \\ 0 & \text{if } Q_j \text{ not in the selected set} \end{cases} \quad (3.3)$$

$$j \in \{0, 1, \dots, m\} \quad (3.4)$$

The purpose of this study is to optimize problem $P = \{K, D_u, T_u, W, C\}$ to find the best set of k questions from the question bank Q where D_u represents the objective level of difficulty, T_u represents the total duration of all of the selected questions, W is the weight coefficient of objective functions, and $C = \{C_1, C_2, \dots, C_r\}$ denotes a set of constraints. D_u , T_u and W parameters required from the user as input. The value of the weight constraint determines the importance of each of the factors of difficulty level and duration. Equal importance will occur when the value of weight is 0.5.

In this research, the main idea is to select questions according to a set of objectives as follows:

- The difficulty level of a question in the set must be equal to the value requested by the user
- The total duration of questions should equal the required duration.

The solution comprises an optimized set of questions, by considering some appropriate properties of each question such that the question set can be selected with the values of the difficulty level and the duration close to the objective values. Consequently, this

results in the optimization of objective functions F_1 and F_2 . The objective functions for this optimization problem are calculated using equations 3.5 and 3.6.

$$F_1 = \frac{\sum_{i=1}^k S_i D_i}{k} - D_u \quad (3.5)$$

$$F_2 = 1 - \frac{\sum_{i=1}^k S_i T_i}{T_u} \quad (3.6)$$

Based on the definitions of the objective functions, the target function of our problem is as follows:

$$\text{Min: } F = W \times F_1 + (1 - W) \times F_2 \quad (3.7)$$

$$\text{Subject to: } W \in (0 \ 1) \quad (3.8)$$

The constraints and conditions required by object functions are:

1. All the questions in the selected set should not have the same level of difficulty.
2. The set of questions should not include repeated questions.
3. The selected set should have the right number of questions requested by the user (Equation 3.9).

$$k - \sum_{j=1}^m S_j = 0 \text{ where } S_j \in S \quad (3.9)$$

NSGA-II Optimization Algorithm: In this section, we provide an overview of the NSGA-II algorithm. NSGA-II is a type of multi-objective evolutionary algorithm in which a population set of chromosomes (solutions) heading to better solutions is widely used in many real-world applications. Among the important features of this algorithm, we can mention using of elitist principle and explicit diversity-preserving mechanism and emphasizing the non-dominated solutions. The principle of the

NSGA-II algorithm is shown in Figure 3.5 according to its non-dominated sorting strategy.

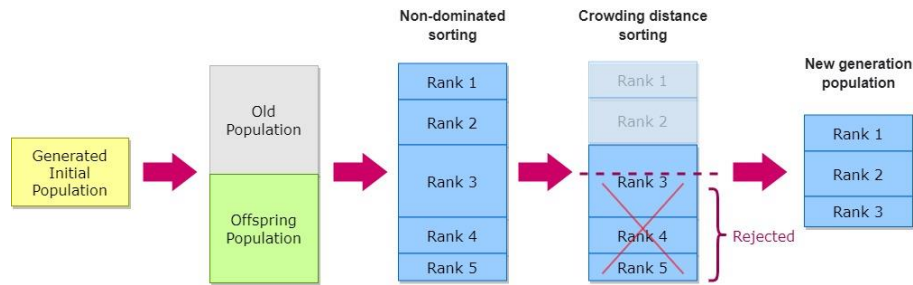


Figure 3.5: Mechanism of NSGA-II algorithm

As shown in the flowchart illustrated in figure 3.6, the main steps of a simple NSGA-II algorithm for multi-objective problems usually start from a randomly produced population in the first generation. All the individuals are classified into different ranks based on non-dominance by calculating the fitness value for each individual. In addition to the fitness value of each individual, crowding distance is calculated too. The crowding distance indicates how far it is from its neighbors and how close it is to them. (Figure 3.7). A larger average crowding distance value will cause better diversity in the population.

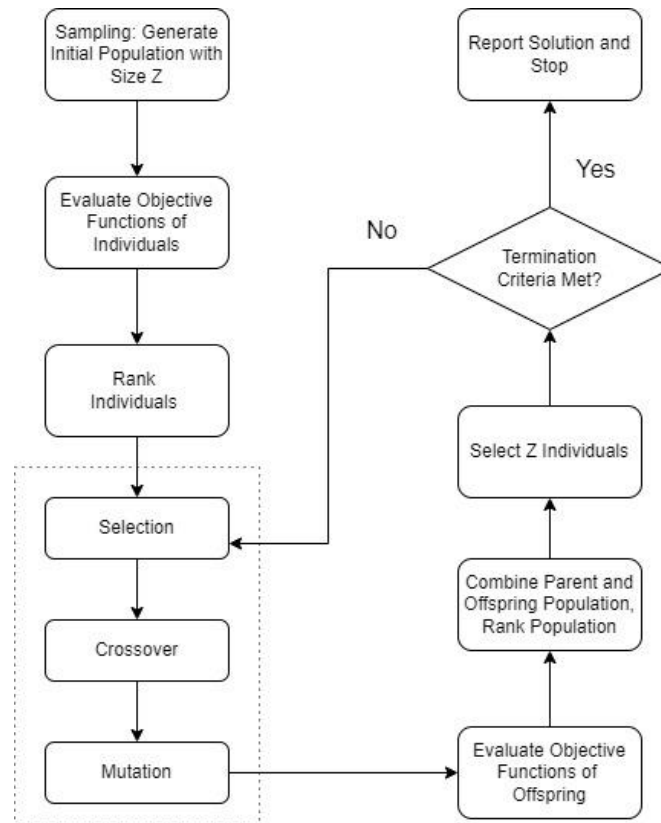


Figure 3.6: Flowchart of NSGA-II

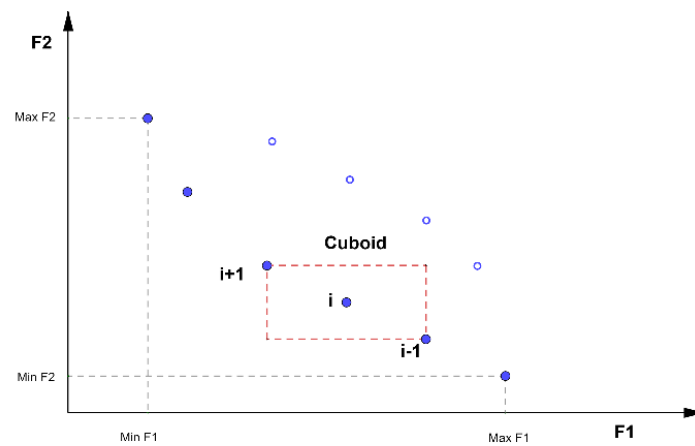


Figure 3.7: Crowding distance

In the next step sorting algorithm applying by using calculated fitness values according to the domination criterion. A selection process is carried out to select the best individuals by a tournament selection with the help of a crowding distance prediction procedure. Next, crossover and mutation operators are performed to create an offspring

population, and fitness values are calculated for the newly generated population. The resulting offspring population is combined with the old population, then a non-dominated sorting is applied to the new combined populations and classify them by fronts and generates the new population according to the ranking of the front (Figure 3.8).

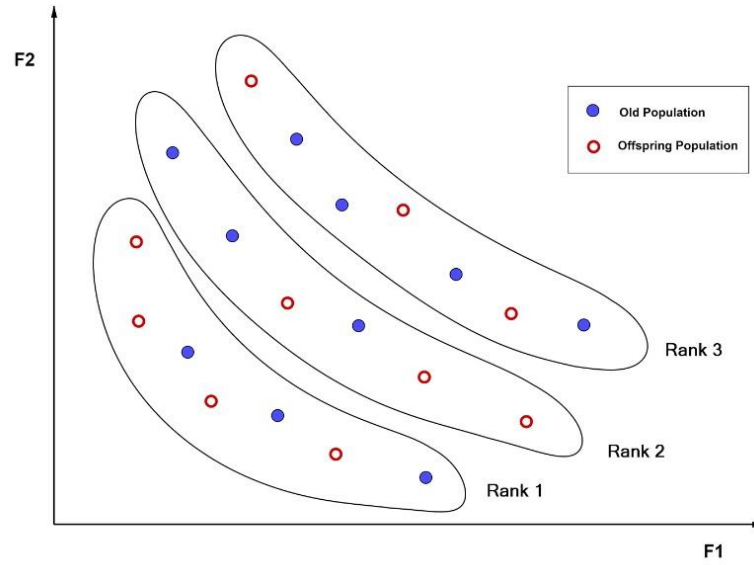


Figure 3.8: Selection mechanism of NSGA-II

Afterward, individuals that will pass on to the next generation are selected. This process is repeated until all the stopping criteria are met. The stopping criteria can be different conditions such as the number of generations or the value of objective functions. As the number of generation or objective function value reaches the defined value, NSGA-II stops and report the last population with their corresponding fitness values and fronts.

Proposed Modified Operators of NSGA-II Optimization Algorithm: To improve the performance of the algorithm on the problem of selecting a set of questions from the question bank, some modifications were made to the original algorithm. Small

changes were made to sampling, crossover, and mutation operators to reduce the algorithm execution time and improve the quality of results.

Sampling: The first step of the NSGA-II algorithm is to generate an initial population in which a set of possible solutions is included. The quality of this population plays a key role in solving an optimization problem by NSGA-II. For any set of questions, we calculate the eligibility level for each question. A higher eligibility level for each question increases the chance of being placed in the initial population. The two-dimensional coordinate system used in this research uses the difficulty level and duration of a question as the two dimensions (Figure 3.9). The difficulty level and duration are expressed as percentages from 0 to 100, which are calculated for the duration variable by considering the maximum value available in the question bank. By plotting the difficulty and duration of a question on this coordinate system, the distance between two points can be calculated. The research defines an ideal point on the coordinate system, which represents a question with the ideal difficulty level and duration. The eligibility level of a question is then calculated based on its distance from the ideal point. For example, a question that is plotted very close to the ideal point would have a high eligibility level, whereas a question that is plotted far from the ideal point would have a low eligibility level. If we consider point A as the ideal question in Figure 3.9, then the eligibility level of each question is directly related to the distance of the point corresponding to that question from the point corresponding to the assumed ideal question.

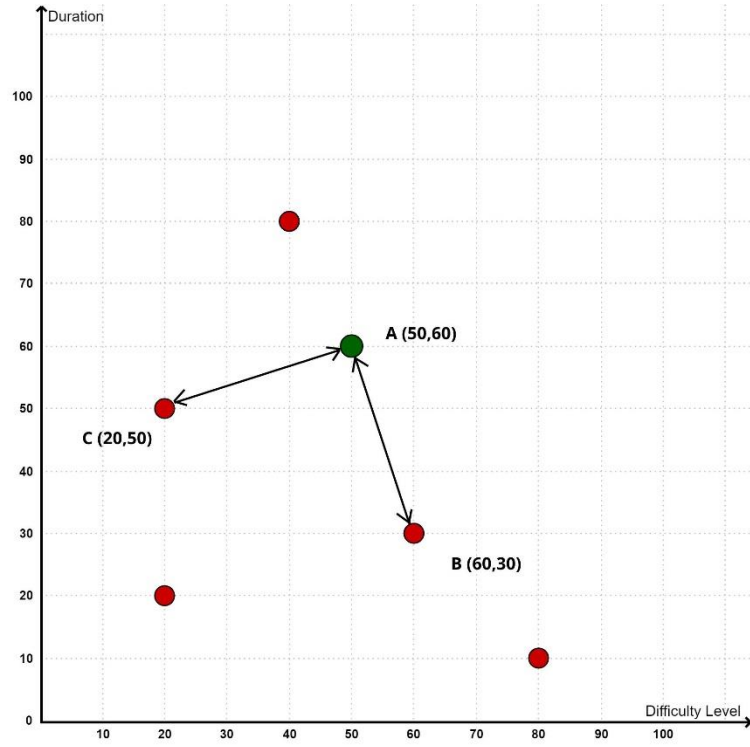


Figure 3.9: Initial population sampling

The distance of each point from the ideal point (E_B) is obtained as follows:

$$d_B = \sqrt{(D_B - D_A)^2 + (T_B - T_A)^2} \quad (3.10)$$

Where D_B is difficulty level and T_B is the duration of point B and $T_A = \frac{T_u}{k}$ and $D_A = D_u$ belongs to point A.

The weight of each question can be calculated as follows:

$$e_B = \frac{1}{d_B} \quad (3.11)$$

Now the initial individuals can be obtained by applying the steps used in the Weighted Random Sampling (WRS) algorithm [157]. Individuals (each corresponding to a set of questions) are obtained by selecting questions randomly from Q using WRS where the weights obtained by calculating eligibility level of each question (Figure 3.10).

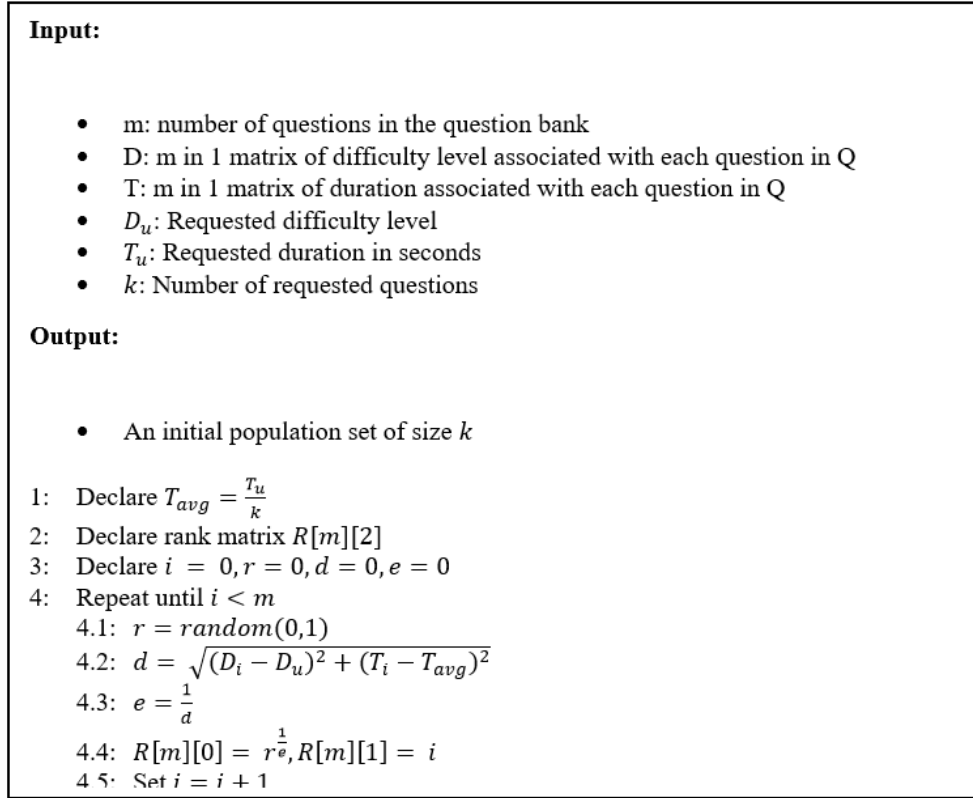


Figure 3.10: Pseudocode of WRS

Crossover: In this study, a modified binary crossover is used to produce a new population. A modified binary crossover takes the values of two parents and then selects from one of the parents randomly by considering their eligibility ranking until enough number of them are selected.

Mutation: The mutation operator is modified to use subset selection from a set and simply removes a number and chooses another one randomly. In our problem, the

mutation operator randomly picks a question that is not selected and adds it to the selection and picks one selected randomly and removes it from the list.

3.8.3 Experiments

In this section, we experiment with the question selection problem to evaluate the performance of our modified algorithm compared with other methods.

Experimental Environment: We now present our experimental results with the aim of showing the efficiency of the proposed algorithm compared with other algorithms. We run all tests on the same computer system to allow a fair comparison. All the runs performed on a server with specifications are listed in Table 3.2. In all experiments explained here, we use Python 3.10 and Pymoo 0.6.0 [158] for the implementation of the algorithms.

Table 3.2: Server configuration used to run tests

Item	Description
Operation System	Microsoft Windows 10 Pro
System Type	64-bit
Processor 1	Intel-Xeon Serie E5-2660 v2 (2.20 GHz)
Processor 2	Intel-Xeon Serie E5-2660 v2 (2.20 GHz)
RAM	16 GB

Method of 5-fold cross-validation applied to validate the performance of each population. By considering the results of the validation method by shifting the population size from 10 to 100 with a step size of 10, a population size of 50 was selected. Two stopping conditions are used in this experiment. One of the conditions is to reach the 1000th generation, and the other one is the value of the objective

function, which must be less than threshold $\varepsilon = 0.002$. We performed these tests on two different question banks with a small and large number of questions. All of the parameters for this experiment are shown in Table 3.3.

Table 3.3: Parameter values for the experiment study

Parameter		Value
Population size		50
Stop Criteria	Maximum Number of Generations	1000
	Objective function value	less than $\varepsilon=0.002$
Number of questions in the question bank		1000, 20000
Number of required questions		10, 100
Level of difficulty		0.5
Required duration (seconds)		900, 9000
The weight coefficient (W)		{0.1, 0.2, .., 0.9}

To test the efficacy of the presented algorithm, the obtained results should be compared with the results of other algorithms. For this purpose, 4 different algorithms were selected and the MOO problem of selecting questions from the question bank was also implemented on them. The algorithms used in this experiment are as follows:

- Eligibility Ranking Non -Dominated Sorting Genetic Algorithm II (ER-NSGA-II)
- NSGA-II [124]
- AGE-MOEA [126]
- SMS-EMOA [125]
- Multi-Objective Genetic Algorithm (MOGA) [159].

To select the crossover and mutation rate (probability) value that can be used in each algorithm, the experiment was repeated for each algorithm for different probability values for crossover and mutation between 0.1 and 0.9 and finally, the optimal values were selected. In every experiment, each execution was repeated 50 times. All of the algorithms used in this experiment are listed in table 3.4 with relevant details. Five factors were considered due to evaluate the results of the experiment. The average execution time of the algorithm to select questions (in seconds), the average value of the objective function for evaluating the quality of solutions, and the average number of generations to reach the solutions.

Table 3.4: MOO algorithms used in the experiment study

Algorithm	Operators			
	Sampling	Selection	Crossover	Mutation
ER-NSGA-II	Modified Random	Tournament Selection [160]	Modified Binary Crossover	Modified Mutation
NSGA-II	Random	Tournament Selection	Two-Point Crossover (Probability=0.9)	Bit-flip mutation [161] (Probability=0.3)
AGE-MOEA	Random	Tournament Selection	Two-Point Crossover (Probability=0.7)	Bit-flip mutation (Probability=0.1)
SMS-EMOA	Random	Tournament Selection	Two-Point Crossover (Probability=0.9)	Bit-flip mutation (Probability=0.1)
MOGA	Random	Tournament Selection	Two-Point Crossover (Probability=0.9)	Bit-flip mutation (Probability=0.1)

Data Collection: In this research, datasets were extracted from the Learning Management System of the Eastern Mediterranean University. This system is based on the free and open-source learning management system written in PHP named

Moodle which is normally used for online education. The database used in this system is MySQL. The question bank of Moodle allows users to create, modify and preview questions in a database and use them in the Quiz or Lesson activity. More than 80,000 multiple-choice questions were extracted from the database to use in this research. Two question banks were created with questions randomly selected from the main question bank. The small question bank contains 1000 and the big one contains 20000 different questions. The distribution of questions in parameters of difficulty level and duration for the small question bank is shown in figure 3.11 and for the large question bank shown in figure 3.12.

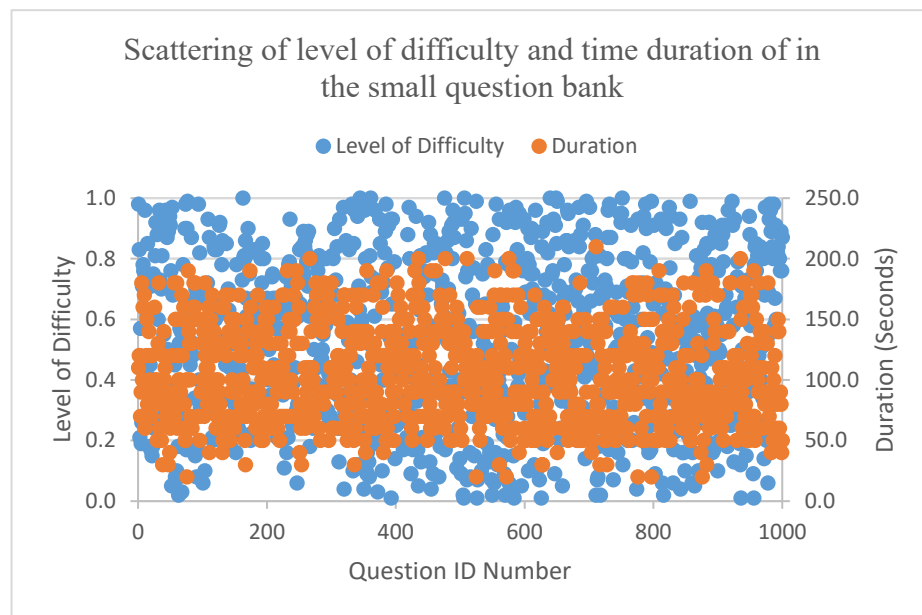


Figure 3.11: Distribution of difficulty level and duration for questions in the small question bank

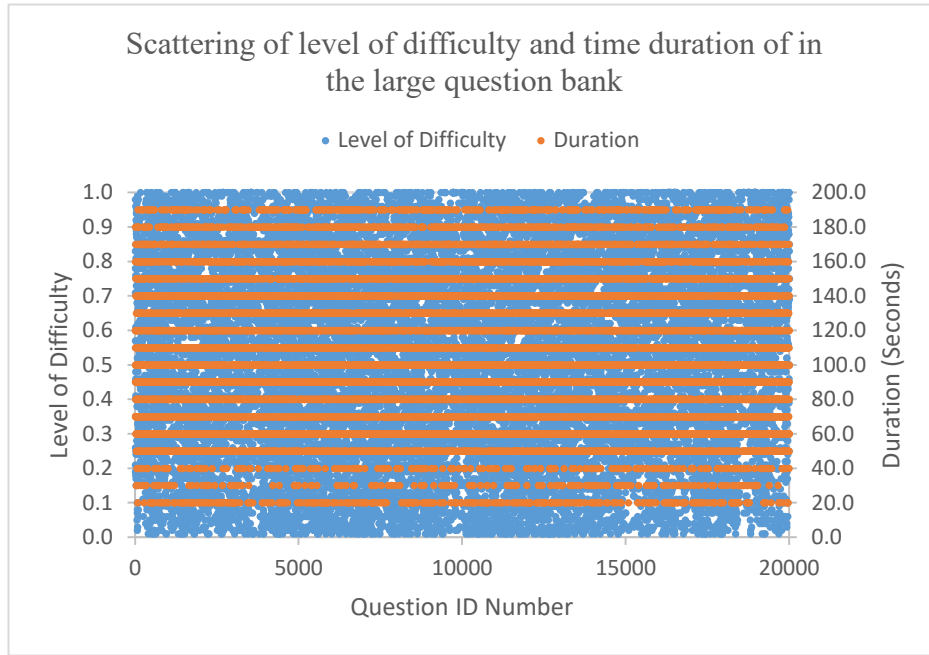


Figure 3.12: Distribution of difficulty level and duration for questions in the large question bank

3.8.4 Results

This section shows the results obtained by applying the proposed and other algorithms to select a certain number of questions from the question bank. To evaluate the performance and efficiency of the algorithms on the target optimization problem, each algorithm was executed 50 times on different weight constraints and different numbers of questions to be selected. Each execution of algorithms reported outputs related to the execution time (ET), objective function value (F), and the number of generations (NG). The results of the executions for the small question bank are shown in Table 3.5 and the large question bank are shown in Table 3.6 and the best results of execution time achieved from algorithms are emphasized in bold. From the results obtained, the following observations can be made:

Observation 1: According to Tables 3.5 and 3.6, no correlation was observed between the value of the weight coefficient (W) and the execution time. Also, there was no correlation between the value of the weight coefficient and the value of the objective function.

Observation 2: In the small question bank, the order of results for execution time obtained from algorithms was the same for both 10 and 100 questions selection. The execution time for our proposed algorithm (ER-NSGA-II) was by far the best. The SMS-EMOA, NSGA-II, and AGE-MOEA are placed in the next ranks respectively. The worst result was obtained from the MOGA. (Figure 13)

Observation 3: In the large question bank, when selecting a small number of questions (10) from the question bank, the order of performance of the algorithms in results for execution time is similar to the small question bank, but in selecting a larger number of questions (100), after our proposed algorithm, which still provided far better results, the AGE-MOEA is placed, and the NSGA-II and the MOGA had weaker performances respectively. The SMS-EMOA had the worst performance in this experiment. (Figure 3.13)

Observation 4: In both small and large question banks, all the algorithms were able to perform well in minimizing the objective function value. Although the results were somewhat close to each other, our proposed algorithm still had the best performance in minimizing the value of the objective function. (Figure 3.14)

Observation 5: The number of generations to reach the final solution for algorithms NSGA-II, AGE-MOEA, SMS-EMOA, and MOGA to select 100 questions is far more than the number of generations for 10 questions, but it is different for the proposed algorithm and does not have a fixed trend. (Figure 3.1)

Table 3.5: Experimental results of testing for small question bank

			ER-NSGA-II			NSGA2			AGE-MOEA			SMS-EMOA			MOGA		
W	QS	NE	ET	F	N G	ET	F	NG	ET	F	NG	ET	F	NG	ET	F	NG
0.1	10	50	0.22	0.0015	9	0.44	0.0018	20	0.43	0.0012	16	0.43	0.0013	19	0.10	0.0014	6
	100	50	0.13	0.0017	6	6.49	0.0018	245	3.28	0.0019	120	13.20	0.0018	441	10.89	0.0019	398
0.2	10	50	0.24	0.0014	10	0.58	0.0002	26	0.39	0.0010	16	0.51	0.0006	22	0.91	0.0012	40
	100	50	0.08	0.0018	4	4.89	0.0008	185	3.55	0.0018	131	2.45	0.0018	89	5.97	0.0011	208
0.3	10	50	0.39	0.0015	16	0.15	0.0012	7	1.65	0.0015	59	0.46	0.0018	19	1.04	0.0006	45
	100	50	0.08	0.0012	4	2.82	0.0016	114	2.03	0.0003	73	5.10	0.0010	179	2.97	0.0015	120
0.4	10	50	0.32	0.0008	13	0.32	0.0016	15	2.51	0.0004	94	0.48	0.0008	21	1.92	0.0004	81
	100	50	0.11	0.0019	5	2.90	0.0014	104	2.38	0.0011	89	3.45	0.0015	105	5.89	0.0019	206
0.5	10	50	0.14	0.0010	6	0.37	0.0005	17	1.98	0.0010	76	1.23	0.0010	51	1.65	0.0010	70
	100	50	0.14	0.0012	6	2.16	0.0016	89	2.23	0.0020	80	2.16	0.0017	82	2.32	0.0014	92
0.6	10	50	0.17	0.0012	7	0.59	0.0018	26	0.31	0.0018	12	0.94	0.0006	39	1.32	0.0018	55
	100	50	0.08	0.0014	4	2.10	0.0015	89	2.66	0.0020	100	2.02	0.0020	74	2.77	0.0018	105
0.7	10	50	0.07	0.0000	3	0.76	0.0014	33	0.20	0.0014	9	0.22	0.0014	11	2.85	0.0014	114
	100	50	0.08	0.0015	4	1.63	0.0010	65	2.15	0.0019	79	2.63	0.0018	83	1.92	0.0010	82
0.8	10	50	0.19	0.0008	8	2.91	0.0016	117	0.60	0.0016	24	0.38	0.0008	16	2.69	0.0008	112
	100	50	0.08	0.0007	4	2.53	0.0018	100	2.47	0.0015	92	3.70	0.0010	128	3.49	0.0019	143
0.9	10	50	0.34	0.0009	14	1.27	0.0018	54	2.29	0.0009	86	1.98	0.0018	80	1.32	0.0018	56
	100	50	0.16	0.0008	7	4.12	0.0015	148	5.94	0.0019	210	5.86	0.0014	172	11.95	0.0019	435

Table 3.6: Experimental results of testing for large question bank

			ER-NSGA-II			NSGA2			AGE-MOEA			SMS-EMOA			MOGA		
W	QS	NE	ET	F	NG	ET	F	NG	ET	F	NG	ET	F	NG	ET	F	NG
0.1	10	50	1.93	0.0003	11	3.28	0.0013	15	2.58	0.0013	11	0.60	0.0019	4	3.00	0.0017	14
	100	50	4.25	0.0018	24	14.18	0.0000	56	42.34	0.0017	160	33.38	0.0012	125	22.21	0.0011	95
0.2	10	50	1.89	0.0004	11	9.35	0.0012	39	1.63	0.0010	8	10.60	0.0012	44	2.72	0.0002	13
	100	50	3.17	0.0011	18	115.24	0.0015	377	23.97	0.0018	90	16.74	0.0009	68	24.91	0.0015	108
0.3	10	50	3.14	0.0003	18	6.23	0.0012	27	17.22	0.0018	65	1.79	0.0003	9	6.52	0.0006	28
	100	50	2.63	0.0012	15	15.97	0.0019	66	15.10	0.0017	56	15.91	0.0019	57	18.28	0.0008	78
0.4	10	50	3.34	0.0008	19	12.60	0.0004	52	6.40	0.0004	26	2.64	0.0016	12	7.65	0.0012	32
	100	50	2.27	0.0019	13	12.73	0.0006	57	42.61	0.0020	153	32.17	0.0015	72	24.78	0.0015	99
0.5	10	50	3.32	0.0015	19	18.83	0.0005	76	12.79	0.0015	51	8.75	0.0005	35	6.61	0.0005	28
	100	50	2.25	0.0015	13	12.94	0.0008	52	19.05	0.0007	73	14.79	0.0011	49	25.77	0.0014	110
0.6	10	50	9.55	0.0006	54	6.00	0.0012	25	13.14	0.0012	52	7.34	0.0006	28	2.07	0.0012	10
	100	50	2.58	0.0018	15	14.44	0.0010	62	27.31	0.0004	99	24.10	0.0011	67	18.71	0.0008	80
0.7	10	50	2.08	0.0014	12	7.81	0.0007	32	4.67	0.0014	19	17.90	0.0014	68	11.15	0.0014	46
	100	50	3.72	0.0018	21	12.19	0.0013	51	74.50	0.0013	245	9.98	0.0020	41	19.98	0.0012	82
0.8	10	50	2.07	0.0016	12	21.63	0.0016	85	9.28	0.0008	37	19.79	0.0016	77	32.12	0.0008	125
	100	50	4.26	0.0014	24	19.15	0.0018	78	27.64	0.0020	107	32.78	0.0016	126	31.61	0.0017	137
0.9	10	50	5.46	0.0009	31	7.48	0.0009	30	9.28	0.0009	37	11.14	0.0018	44	46.72	0.0018	183
	100	50	4.39	0.0002	25	34.85	0.0019	148	48.28	0.0017	176	43.95	0.0020	125	31.31	0.0019	126

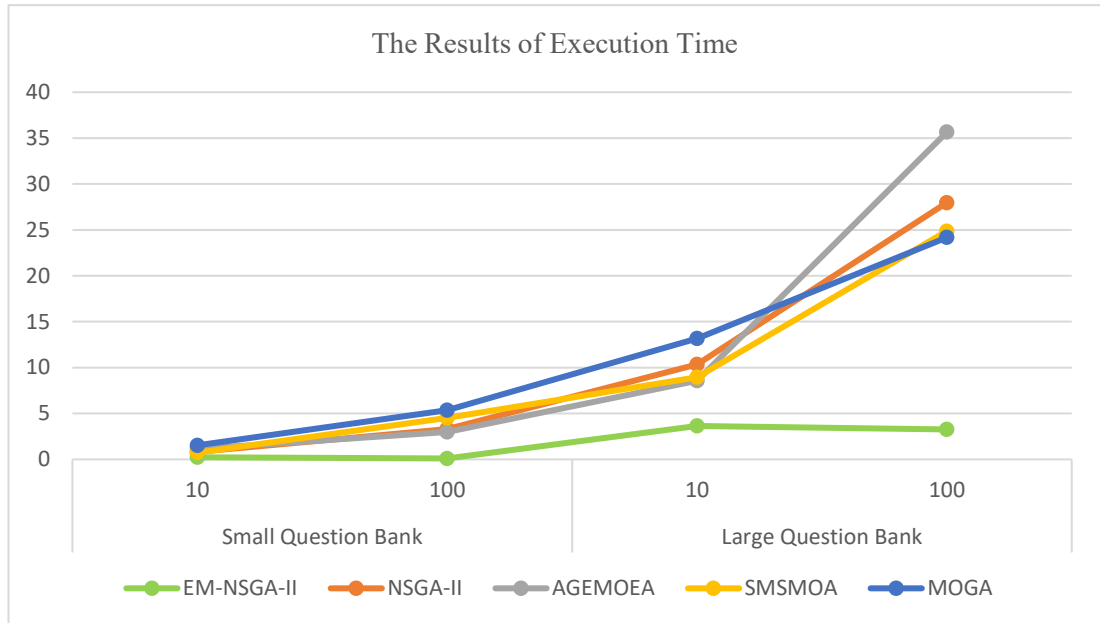


Figure 3.13: The results of the execution time

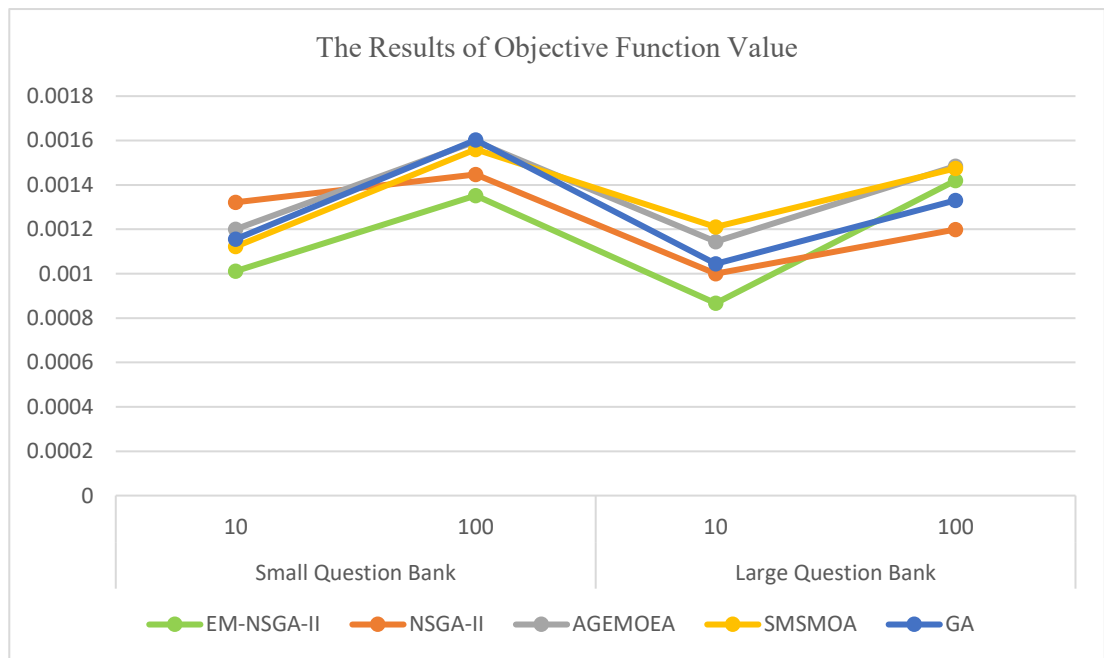


Figure 3.14: The results of objective function value

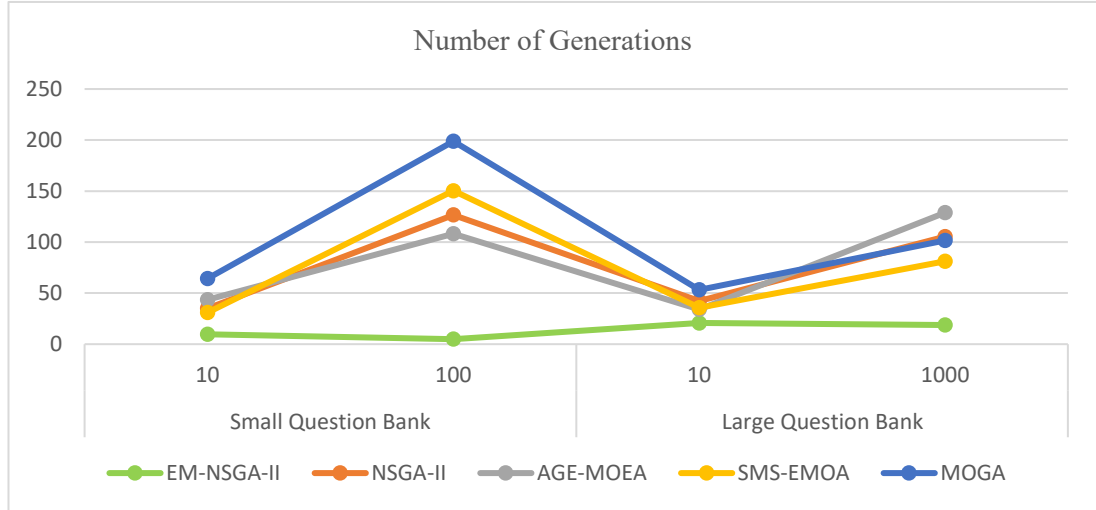


Figure 3.15: Number of generations

3.8.5 Discussion

This section summarizes the findings of our study and the contributions made to the topic. In this study, we proposed a modified NSGA-II algorithm to implement on optimization problem of selecting questions from the question bank. The results of the experiment found clear support for our proposed ER-NSGA-II method and our method was the one that obtained the most robust results in different criteria. The execution time of the proposed algorithm was significantly better than other algorithms in both question banks, and the reason could be that the generated initial population was chosen close to the solution and shortened the path to the final solution by using a modified crossover. The MOGA had the worst result in terms of execution time, which shows the insufficient efficiency of the simple version of this algorithm in our experiment. One of the remarkable points in the obtained results is that with the increase in the population of the question bank and the number of selected questions, the efficiency of the SMS-EMOA decreases drastically and its performance in terms of execution time is even lower than the MOGA.

The results obtained from the execution of all algorithms on both question banks prove that with the increase in the population, the duration of execution increases in all algorithms, which can be the reason for the increase in the number of generations to reach the final solution.

In optimizing the minimization of the objective functions by ignoring the execution time parameter, all algorithms performed well and succeeded in reaching the final solution in all experiments, although the proposed algorithm had a relatively better result for the optimization of the problem than the rest of the algorithms in both question banks.

Also, it can be seen from the results that, except in the proposed algorithm, the number of generations to reach the final solution is more than the population of the question bank depending on the number of questions requested for selection, and with the increase in the number of requested questions from 10 to 100, the number of generations also increases significantly. In our proposed algorithm, this number does not depend on the parameters and provides better results.

From all the assessments, it is proved that the proposed algorithm for solving the problem of question selection from the question bank is completely superior to other algorithms.

3.8.6 Conclusion

One of the main purposes of the current study was to propose a modified NSGA-II algorithm and compare its efficacy with several important multi-objective evolutionary algorithms to optimize the multi-objective problem of selecting a certain number of questions from the question bank by applying criteria such as difficulty

level and duration. Another aim of this study was to investigate the effects of the weight coefficient for objective functions on the results. The results of this study show that the proposed algorithm was more efficient in terms of execution time, the value of the objective functions, and the number of generations, and the weakest overall efficacy was for the MOGA. The second major finding was that increasing the number of selected questions and the population of the question bank both increase the duration of execution to finding the solution and the weight coefficient made no significant effect on results. These findings provide strong support for our proposed algorithm and make several contributions to the current literature. First, it provides a new modified NSGA-II algorithm that can be implemented on other multi-objective optimization problems and its efficiency can be measured. Second, we also implemented and compared other important multi-objective evolutionary algorithms on the problem, many of these algorithms were implemented on this problem for the first time. Further research is needed to confirm the efficacy of our proposed algorithm. Future research should implement hybrid algorithms on the problem and compare the results.

3.9 Question Set Generation

The selection of questions to be presented to a learner is a crucial task that can significantly impact the effectiveness of the learning process. To optimize the execution time and accuracy of the questions, we used our proposed ER-NSGA-II algorithm which takes into account multiple factors that can influence the performance of the system.

Proposed system allows users to add their own questions or import them from external systems like learning management systems. The difficulty level of the questions in the question bank is regularly updated based on the assessment results, allowing the system to continuously refine and improve the accuracy of the question set selection process. (Figure 3.16)

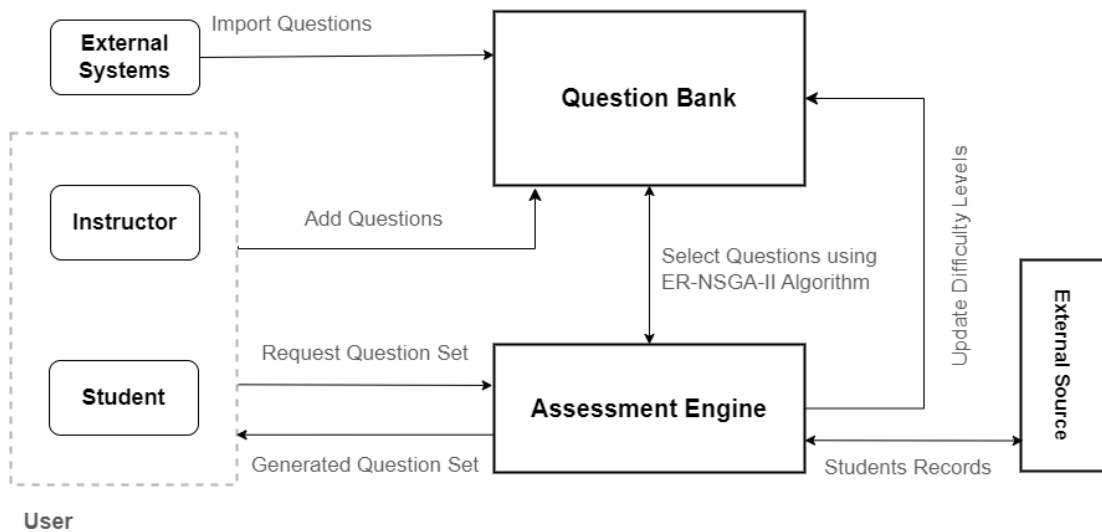


Figure 3.16: Question set generation

Users can request a question set by specifying various criteria such as difficulty level, question count, and total duration. The assessment engine then uses the ER-NSGA-II optimization algorithm to select the optimal question set based on these criteria. In order to get personalized results, these criteria can be based on student's academic records and performance and these data can be obtained from external sources. The selected questions are then presented to the user for assessment.

This process of question set selection using the ER-NSGA-II optimization algorithm ensures that the learner is presented with a customized and effective set of questions, tailored to their specific needs and capabilities.

3.10 Technical Aspects

The technical aspects involve the development and operation of the system's software and hardware components, as well as the infrastructure and protocols that enable the system to function. To start the implementation phase, we conducted an analysis of the technical requirements that would be necessary for the development process. We also examined the technical architectures of previous projects to identify their strengths and weaknesses.

The system follows a client-server architecture, in which the system is made up of two main components: a client-side component that is run by the user, and a server-side component that is run by the system. The client-side component is typically implemented as a web application that is accessed through a web browser and is responsible for displaying the user interface and handling user interactions. The server-side component is responsible for handling requests from the client-side component, processing data, and returning responses. Communication between the client and server is typically handled using a secure standardized protocol such as HTTPS.

For the proposed system, we used various tools to support this approach, as listed in Table 3.7. These tools helped us to develop and implement the system in a reliable, efficient, and effective manner.

Table 3.7: Tools used in the proposed system

Tool	Type	Description
.NET Core	Framework	A free, open-source, cross-platform framework for developing web applications, cloud services, and other types of software
Python	Programming Language	A high-level, interpreted programming language that is widely used for web

		development, data analysis, and scientific computing
Microsoft SQL Server	Database management system	As a widely used database management system that can be used to store and manage data. A range of features and tools offered by it to help ensure the integrity, performance, and security of the data, which can be important for the reliable and effective operation of the system.
Visual Studio	Integrated development environment (IDE)	An IDE for developing .NET applications, which includes tools for editing, debugging, and testing code, as well as for managing source code and other project resources
HTML	Markup language	A markup language for creating and formatting web pages
CSS	Style sheet language	A style sheet language for describing the look
JavaScript	Programming language	A high-level, interpreted programming language that is commonly used for creating interactive web pages and applications.
Pymoo	Library	A library for optimization in Python that provides tools for solving various types of optimization problems, including multi-objective optimization, constrained optimization, and global optimization

3.11 User Interface

The UI for the proposed system is designed to be intuitive and user friendly, with a clean and modern look and feel. The main screen consists of a navigation menu on the left, which allows users to access the different features and functions of the system and a main content area on the right. (Figure 3.17)

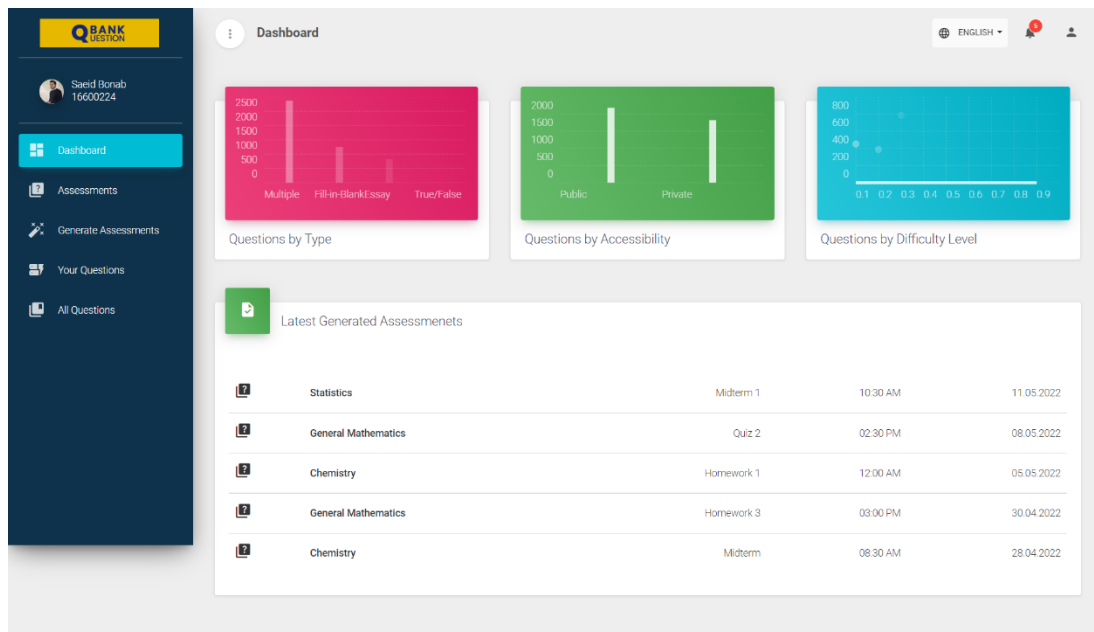


Figure 3.17: Dashboard page

The navigation menu includes options such as "Assessments", "Generate Assessments", "Your Questions", and "All Questions" which allow users to manage their own questions, create new questions, search for questions created by other users publically and manage assessments, respectively. The main content area in the dashboard displays the selected feature or function, such as a list of the user's latest generated assessments and statistical charts.

The UI also includes a top bar with user profile, notifications, and settings options, as well as a language selection select box that allows users to select the language they prefer to use.

The "Your Questions" page allows users to view and manage their own questions in the system. The page includes a search box that allows users to list their added questions. It is also possible to download, edit, delete and view the details of the question. (Figure 3.18)

Q BANK QUESTION

Saeid Bonab
16600224

Dashboard

Assessments

Generate Assessments

Your Questions

All Questions

Dashboard

Your Private Questions

+ ADD NEW QUESTION

Keyword

Type

Choose option

Min. Difficulty Level

Max. Difficulty Level

Min. Duration

Max. Duration

Subject

Choose option

Topic

Choose option

SEARCH

Type	Topic	Question	Date	Difficulty	Duration	Actions
Multi-Choice	Statistics	The runs scored by a batsman in 5 ODIs ar...	10:30 AM 11 05 2022	0.3	30	
Descriptive	Statistics	Find the mode and median of the 9 conse...	08:10 AM 01 05 2022	0.3	60	
Multi-Choice	Statistics	If the probability of hitting an object is 0.8, ...	02:10 PM 08 04 2022	0.4	20	
Multi-Choice	Probability	An event in the probability that will never b...	08:20 AM 29 03 2022	0.7	120	
Multi-Choice	Probability	What is the probability of getting a sum as ...	10:45 AM 23 03 2022	0.9	180	
Multi-Choice	Probability	In a box, there are 8 orange, 7 white, and 6 ...	09:15 AM 13 02 2022	0.4	45	

Figure 3.18: Your questions page

The "Add New Question" page which is accessible from Your Questions page allows users to create new questions in the system. The page includes a form with fields to enter the question text, subject area, topic, and any additional details or instructions. (Figure 3.19)

Q BANK LIFTION

Saeid Bonab
16600224

- Dashboard
- Assessments
- Generate Assessments
- Your Questions**
- All Questions

Dashboard

+ Add New Question

Accessibility: Choose option

Difficulty Level:

Duration:

Question Type: Choose option

Subject: Choose option

Topic: Choose option

Type

File Edit View Insert Format

↶ ↷ Paragraph **B** *I* [Text Alignment Icons]

p

Label 1

File Edit View Insert Format

↶ ↷ Paragraph **B** *I* [Text Alignment Icons]

☐ Correct Answer

p

Label 2

File Edit View Insert Format

↶ ↷ Paragraph **B** *I* [Text Alignment Icons]

☐ Correct Answer

p

Label 3

File Edit View Insert Format

↶ ↷ Paragraph **B** *I* [Text Alignment Icons]

☐ Correct Answer

p

Label 4

File Edit View Insert Format

↶ ↷ Paragraph **B** *I* [Text Alignment Icons]

☐ Correct Answer

p

ADD OPTION

ADD

Figure 3.19: Add new question page

The "All Questions" page allows users to view and search all of the public questions in the system. You can download the listed questions or view their details. (Figure 3.20)

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16600224

- Dashboard
- Assessments
- Generate Assessments
- Your Questions
- All Questions

Dashboard

Public Questions

Keyword

Type

Choose option

Min. Difficulty Level

Max. Difficulty Level

Min. Duration

Max. Duration

Subject

Choose option

Topic

Choose option

SEARCH

Type	Topic	Question	Date	Difficulty	Duration	Actions
Multi-Choice	Soft Computing	How many types of random variables are there in Fuzzy logic?	23.05.2022	0.8	60	
Multi-Choice	Soft Computing	Which of the following represents the values of set membership?	10.05.2022	0.7	45	
Multi-Choice	Soft Computing	What is the name of the operator in fuzzy set theory, which is found to b...	09.05.2022	0.8	90	
Multi-Choice	Soft Computing	Which of the following is offered by the Bayesian network?	01.05.2022	0.5	60	
Multi-Choice	Soft Computing	Name the algorithms that acquire from complex environments to gener...	29.04.2022	0.8	45	

EXPORT ALL

1 2 3 4 5

Figure 3.20: All questions page

The "Assessments" page contains all the assessments that have already been generated and saved by the user. The user can search and list the questions. It is also possible to preview, download and remove the assessments. (Figure 3.21)

Latest Generated Assessments						
Search						
	Statistics	Midterm 1	10:30 AM	11.05.2022		
	General Mathematics	Quiz 2	02:30 PM	08.05.2022		
	Chemistry	Homework 1	12:00 AM	05.05.2022		
	General Mathematics	Homework 3	03:00 PM	30.04.2022		
	Chemistry	Midterm	08:30 AM	28.04.2022		
	Statistics	Quiz	09:30 AM	14.03.2022		
	Combinatorics	Quiz	11:30 AM	08.01.2022		

Figure 3.21: Assessments page

The "Generate Assessment" page is an important feature of the system, as it allows users to generate custom assessments using the questions in the system. The page includes two forms with several fields and controls that the user can use to specify the criteria for the assessment. The first form is embedded for use by all users, where all criteria can be specified. In the second form, which is specifically for students, fewer criteria can be selected, instead, the system adjusts the rest of the criteria using updated data from external systems such as the learning management systems. This data can include students' academic performance. One of the key fields in the forms is the subject area field, which allows the user to select the subject area or subject areas that they want the assessment to cover. It is also possible to choose a specific topic from the subset of the subjects. Another important field in both forms is the number of questions field, which allows the user to specify how many questions they want the assessment to include. The user can enter a specific number of questions. It is also possible to choose the level of difficulty of the questions and the total duration determined for the assessment in the first form, and it helps the accuracy of the selected questions for the target assessment. In addition to these fields, this page includes a

number of controls and options that the user can use to further refine the assessment. For example, the user can specify constraints or preferences for the type of questions, or they can select the accessibility of questions to include in the assessment. Once the user has specified the criteria for the assessment, they can generate it to see the set of selected questions. If the user chooses to save the assessment, it will be stored in their "Assessments" list but will not be visible to other users. If the user chooses to export, it will download the selected questions in many formats. (Figure 3.22)

Other available pages include a login page, user profile, and notifications pages, which are designed in a user-friendly manner.

Q BANK

Saeid /ionab
16600224

Dashboard

Assessments

Generate Assessments

Your Questions

All Questions

MyAssistant

Dashboard

Generate Assessment

Number Of Questions

Difficulty Level

Total Duration

Type

Choose option

Accessibility

Choose option

Subject

Choose option

Topic

Choose option

GENERATE

Generate Personalized Assessment

Number Of Questions

Type

Choose option

Accessibility

Choose option

Subject

Choose option

Topic

Choose option

GENERATE

10
Number Of Questions

900
Total Duration

0.6
Difficulty Level

EXPORT AS EXCEL

EXPORT AS CSV

EXPORT AS TEXT

Assessment Name

SAVE

☒	Type	Topic	Question	Difficulty	Duration	View
☒	Multi-Choice	Probability	The formula for finding the mean of the binomial distribution is -	0.6	60	
☒	Multi-Choice	Probability	How many parameters in the binomial distribution?	0.6	120	
☒	Multi-Choice	Probability	Which of the following can be the probability of an event?	0.6	90	
☒	Multi-Choice	Probability	If three coins are tossed simultaneously, what is the probability of getting two heads...	0.6	120	
☒	Multi-Choice	Probability	The probability of winning the first prize in a lottery of a girl is 8/100. If the total of 6...	0.6	60	
☒	Multi-Choice	Probability	There are 3 blue socks, 5 brown socks, and 4 white socks in a drawer. If two socks a...	0.6	120	
☒	Multi-Choice	Probability	The probability of randomly selecting a rotten apple is 0.18 from the heap of 900 ap...	0.6	90	
☒	Multi-Choice	Probability	If a number is selected at random from the first 100 natural numbers, what will be th...	0.6	120	
☒	Multi-Choice	Probability	What will be the number of events if 10 coins are tossed simultaneously?	0.6	60	
☒	Multi-Choice	Probability	Four dice are thrown simultaneously. What will be the probability that all of them hav...	0.6	60	
☒	Multi-Choice	Probability	A card is drawn from a pack of 52 cards. What is the probability of getting a non-fac...	0.6	90	

Figure 3.22: Generate assessment page

Chapter 4

EXPERIMENTAL RESULTS

4.1 Testing and Evaluation

Testing is a crucial component of web and software development, with the goal of identifying defects in the application, verifying that it meets requirements, and potentially uncovering new requirements. When done correctly, testing can significantly enhance the application through the identification and resolution of issues. The application was evaluated 50 times per different criteria. The primary aim of the testing was to identify problems with the application and discover any new functional requirements or potential modifications to existing functional requirements.

The main issues identified are listed below:

Accuracy of question difficulty levels: One issue that could arise in the system is the accuracy of the difficulty level assigned to each question. If the difficulty level is not properly calibrated, the system may present learners with questions that are either too easy or too difficult, which can negatively impact the effectiveness of the learning process.

Accurate question duration: Ensuring that the duration assigned to each question is accurate is important for the effectiveness of the question bank system. If the duration is not properly calibrated, learners may be presented with questions that take too long or too little time to complete. It is important to regularly review and update the duration

of questions in the question bank to ensure that they are accurately reflected in the system.

Lack of dynamic questions: By enabling users to create and use dynamic questions in assessments, the system can expand its focus to include a wider range of topics and skills, improving the overall coverage of the question bank.

Coverage of the question bank: It is important to ensure that the question bank contains a diverse range of questions that cover a wide range of topics and skills. If the question bank is too narrow in its focus, it may not provide an effective learning experience for all learners.

The developed system is currently hosted on GitHub and will be made available to the public upon the publication of the thesis. Even though the application is already deployed and functioning, there is still a significant amount of work to be completed. This includes addressing issues discovered during user testing, identifying solutions to the application's drawbacks, and proposing new functionality.

4.2 Experiment Environment

To evaluate the performance of our system, we conducted experiments in a controlled environment using a variety of test cases. The experimental setup consisted of details proposed in Tables 3.2 and 3.3. The experimental environment was designed to provide a realistic and controlled setting for evaluating the performance of the system. It allowed us to accurately measure the system's performance and identify any areas for improvement.

The data collected for the experiment is in accordance with the conditions mentioned in chapter 3, and the number of questions in the question bank is 14,000 questions. The distribution of questions in the question bank is shown in Figures 4.1, 4.2, and 4.3 according to the three variables of the topic, duration, and difficulty level.

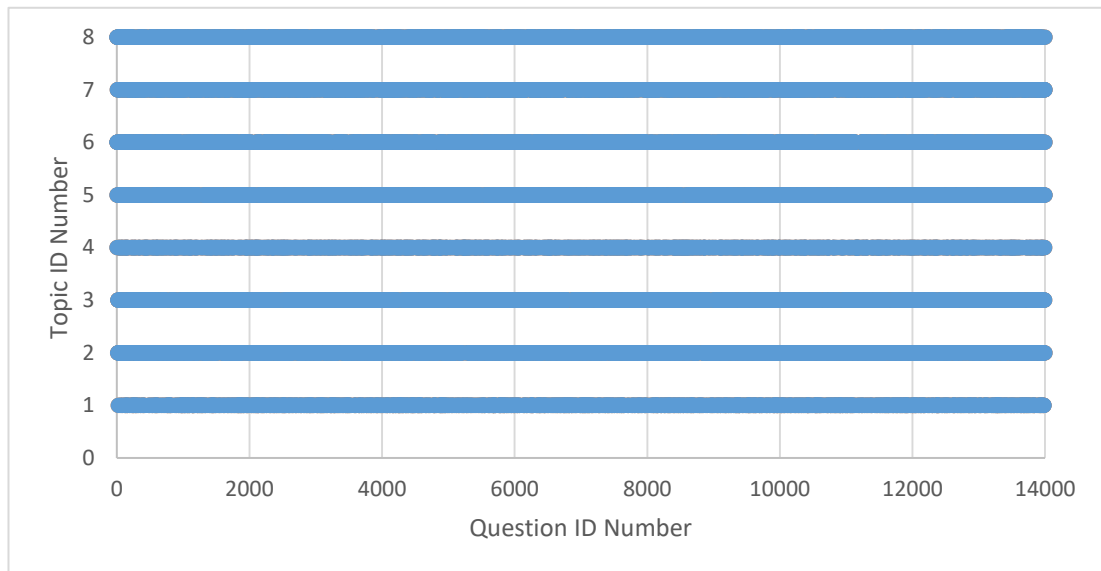


Figure 4.1: Distribution of topics for questions in the question bank

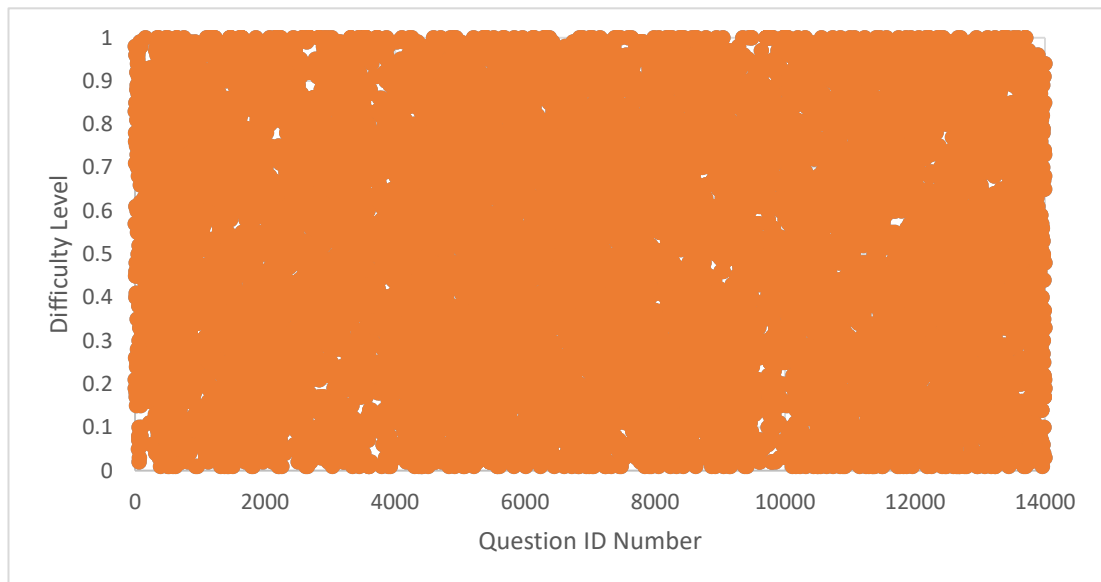


Figure 4.2: Distribution of difficulty level for questions in the question bank

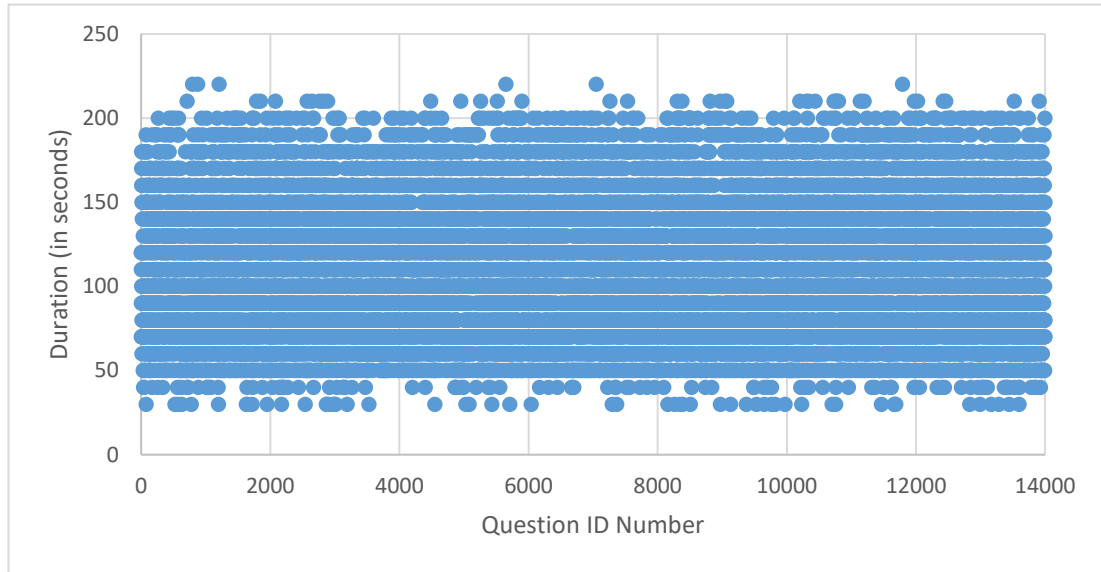


Figure 4.3: Distribution of duration for questions in the question bank

4.3 Results

The experiment was executed 50 times for each difficulty level and different durations, with the goal of selecting 8 questions from different topics in the target question bank. The results showed that all of the tests were completed successfully and there were no errors during the generation of question sets. This suggests that our system was able to effectively select a diverse range of questions from the available topics and generate question sets that met the specified criteria. However, it is important to note that the success of the question-generation process does not necessarily indicate that the system is meeting all of its desired goals. In order to more fully assess the effectiveness of the system, additional measures may need to be taken to evaluate how well the selected questions are aligned with users' individual learning needs and how well the system is able to adapt to changes in these needs over time. This could involve collecting and analyzing data on users' responses to the questions presented by the system, as well as conducting user surveys or focus groups to gather more detailed feedback on the system's performance. By using a combination of quantitative and

qualitative data, it will be possible to more fully understand the strengths and weaknesses of the question bank system and identify any areas for improvement.

4.4 Drawbacks and Planned Improvements

In this section, we will outline the main drawbacks of the proposed system and describe the steps that we are taking to address these issues and improve the system.

One potential drawback of the system is that it requires a significant amount of upfront work to set up and populate the question bank with a diverse range of content. This can be time-consuming and resource-intensive, particularly if the system is being implemented on a large scale.

To address the issue of upfront setup time and resource intensity, we plan to develop automated tools and processes to streamline the process of populating the question bank with a wide range of content. This will involve leveraging existing content sources and adopting best practices for curating and organizing the questions in the bank.

Another potential drawback is that the system may not always be able to accurately predict and select the most appropriate questions for each individual user. This could result in a less effective learning experience for some users, particularly if they are consistently presented with questions that are too easy or too difficult.

To improve the accuracy of question selection, we plan to implement machine learning algorithms that can more accurately predict the most appropriate questions for each individual user based on their past performance and learning needs. This will involve

collecting and analyzing data on users' responses to questions in order to continuously update and refine the prediction models.

Chapter 5

DISCUSSIONS, CONCLUSION, AND FUTURE WORK

5.1 Discussion

One of the main objectives of this study was to analyze the weaknesses of online learning and assessments in order to identify areas for improvement. Online learning and assessments have become increasingly popular in recent years, but there are also several challenges and limitations that must be addressed in order to ensure their effectiveness.

In this study, we conducted research on students' level of satisfaction from online learning and their academic achievements during online learning in order to understand the strengths and weaknesses of this mode of instruction. The results of this study showed acceptable levels of satisfaction regarding online learning among Eastern Mediterranean University students. The participants reported that they preferred online learning over traditional face-to-face learning, and cited flexibility in time and place and ease of access to resources as the most important factors in this preference. The majority of students also indicated a desire to continue using online learning in the future. However, the results also showed a slight drop in students' academic achievements during the COVID-19 pandemic period. This highlights the need for improved assessment methods in order to better support student learning and achievement in an online setting. In order to address these weaknesses, it will be important to develop new approaches and technologies that can more effectively

support online learning and assessment. This might include developing more interactive and personalized learning platforms.

Another objective of this study was to investigate the ability to collect questions into a question bank. A question bank is a collection of pre-prepared questions that can be used for testing or assessment purposes. By collecting questions into a question bank, it is possible to more efficiently and effectively administer assessments and ensure that a diverse range of content is covered. However, collecting questions into a question bank can be a time-consuming and resource-intensive process, particularly if the question bank is intended to cover a wide range of topics or skills. It is also important to ensure that the questions in the bank are well-written, accurate, and relevant to the intended audience.

The final objective of this study was to examine the ability to extract questions at an appropriate difficulty level and total duration using multi-objective optimization methods. To address this objective, we proposed a multi-objective optimization algorithm named ER-NSGA-II that is specifically designed to optimize the results for the generation of question sets. The ER-NSGA-II algorithm optimizes both the execution time and the objective function value, ensuring that the generated question sets are both efficient and effective in meeting the specified criteria. Our results showed that the ER-NSGA-II algorithm had significantly better results than other similar algorithms in terms of both execution time and objective function value. This suggests that the ER-NSGA-II algorithm is a highly effective and efficient approach for optimizing the selection of questions at the appropriate difficulty level and total duration. Our results showed that the proposed system was tested successfully and is usable. In addition, the system was successful in generating a set of questions

considering the specified criteria, indicating that it is able to effectively extract and present a range of questions at the appropriate difficulty level and total duration.

5.2 Conclusion and Future Work

In conclusion, this study has analyzed the strengths and weaknesses of online learning and assessments in order to identify areas for improvement. The results of the study showed that Eastern Mediterranean University students generally had acceptable levels of satisfaction with online learning, and preferred it to traditional face-to-face learning due to its flexibility and ease of access to resources. However, the results also showed a slight drop in students' academic achievements during the COVID-19 pandemic period, highlighting the need for improved assessment methods in the online setting. To address these weaknesses, the development of new approaches and technologies, such as more interactive and personalized learning platforms, may be necessary. One of the main objectives of the study was to investigate the use of a question bank as a tool for generating assessments. The results of the study showed that collecting questions into a question bank can be resource-intensive, but is important in ensuring a diverse range of content is covered. The study also examined the use of a multi-objective optimization algorithm, named ER-NSGA-II, as a method for selecting questions at the appropriate difficulty level and total duration for an assessment. The results showed that the ER-NSGA-II algorithm was significantly more effective and efficient than other similar algorithms in optimizing these criteria.

There are many opportunities for further improvement and development of question bank systems. One potential area for future work is the integration of the question bank system with popular learning management systems. By integrating with platforms such as Moodle or Blackboard, students and educators can access the question bank and

assessments within the same environment as their course materials and grades. This would provide a more seamless and convenient experience for users.

Another area of potential improvement is personalization and adaptive learning. Machine learning algorithms could be used to identify patterns in how students answer questions and adjust the difficulty of future questions accordingly. This would allow the system to tailor the questions and assessments to each individual student's strengths, weaknesses, and learning goals, leading to a more effective and efficient learning experience.

Collaborative learning and peer review could also be incorporated into the question bank system. Students could share questions and review each other's answers, providing a valuable opportunity for them to learn from and give feedback to their peers. A peer review system could be implemented, allowing students to provide feedback on their peers' work and receive feedback in return.

REFERENCES

- [1] S. Greiff and R. Martin, “Computer-Based Testing,” in *Education*, Oxford University Press, 2014. doi: 10.1093/obo/9780199756810-0031.
- [2] J. Carbonell, “AI in CAI: An Artificial-Intelligence Approach to Computer-Assisted Instruction,” in *IEEE Transactions on Man Machine Systems*, Dec. 1970, vol. 11, no. 4, pp. 190–202. doi: 10.1109/TMMS.1970.299942.
- [3] C. W. Cook and C. Sonnenberg, “Technology and Online Education: Models for Change,” *Contemp. Issues Educ. Res.*, vol. 7, no. 3, pp. 171–188, 2014.
- [4] Z. Chen, Y. Wang, and Y. Bai, “Personalized Question Bank Research Based on Particle Swarm Optimization,” in *Proceedings of the 2019 International Conference on Mathematics, Big Data Analysis and Simulation and Modelling (MBDASM 2019)*, Paris, France, 2019. doi: 10.2991/mbdasm-19.2019.25.
- [5] L. Gardner, D. Sheridan, and D. White, “A web-based learning and assessment system to support flexible education: A web-based learning and assessment system,” *J. Comput. Assist. Learn.*, vol. 18, no. 2, pp. 125–136, Jun. 2002, doi: 10.1046/j.0266-4909.2001.00220.x.
- [6] T. H. Wang, K. H. Wang, W. L. Wang, S. C. Huang, and S. Y. Chen, “Web-based Assessment and Test Analyses (WATA) system: development and evaluation: WATA: Development and evaluation,” *J. Comput. Assist. Learn.*, vol. 20, no. 1, pp. 59–71, Feb. 2004, doi: 10.1111/j.1365-2729.2004.00066.x.

- [7] M. Z. Rashad, M. S. Kandil, A. Hassan, and M. Zaher, “An Arabic Web-Based Exam Management System,” 2010.
- [8] V. K. Purohit *et al.*, “Design of adaptive question bank development and management system,” in *2012 2nd IEEE International Conference on Parallel, Distributed and Grid Computing*, Dec. 2012, pp. 256–261. doi: 10.1109/PDGC.2012.6449828.
- [9] S. A. Zahorian, V. K. Lakdawala, O. R. Gonzalez, S. Starsman, and J. F. Leathrum, “Question model for intelligent questioning systems in engineering education,” in *31st Annual Frontiers in Education Conference. Impact on Engineering and Science Education. Conference Proceedings (Cat. No.01CH37193)*, Reno, NV, USA, 2001, vol. 1, pp. T2B-7-T2B-12. doi: 10.1109/FIE.2001.963871.
- [10] P. Padayachee, S. Wagner-Welsh, and H. Johannes, “Online assessment in Moodle: A framework for supporting our students,” *South Afr. J. High. Educ.*, vol. 32, no. 5, Oct. 2018, doi: 10.20853/32-5-2599.
- [11] J. Hoofman and E. Secord, “The Effect of COVID-19 on Education,” *Pediatr. Clin. North Am.*, vol. 68, no. 5, pp. 1071–1079, Oct. 2021, doi: 10.1016/j.pcl.2021.05.009.
- [12] V. J. García-Morales, A. Garrido-Moreno, and R. Martín-Rojas, “The Transformation of Higher Education After the COVID Disruption: Emerging

Challenges in an Online Learning Scenario,” *Front. Psychol.*, vol. 12, Feb. 2021, doi: 10.3389/fpsyg.2021.616059.

[13] G. A. Berg and M. Simonson, “distance learning,” *Encyclopedia Britannica*. Nov. 07, 2016. Accessed: Aug. 15, 2022. [Online]. Available: <https://www.britannica.com/topic/distance-learning>

[14] C. Roddy *et al.*, “Applying Best Practice Online Learning, Teaching, and Support to Intensive Online Environments: An Integrative Review,” *Front. Educ.*, vol. 2, Nov. 2017, doi: 10.3389/educ.2017.00059.

[15] H. Cai and I. King, “Education Technology for Online Learning in Times of Crisis,” in *2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, Dec. 2020, pp. 758–763. doi: 10.1109/TALE48869.2020.9368387.

[16] J. S. Barrot, I. I. Llenares, and L. S. del Rosario, “Students’ online learning challenges during the pandemic and how they cope with them: The case of the Philippines,” *Educ. Inf. Technol.*, vol. 26, no. 6, pp. 7321–7338, Nov. 2021, doi: 10.1007/s10639-021-10589-x.

[17] M. P. A. Murphy, “COVID-19 and emergency eLearning: Consequences of the securitization of higher education for post-pandemic pedagogy,” *Contemp. Secur. Policy*, vol. 41, no. 3, pp. 492–505, Jul. 2020, doi: 10.1080/13523260.2020.1761749.

- [18] C. Neuhauser, "Learning Style and Effectiveness of Online and Face-to-Face Instruction," *Am. J. Distance Educ.*, vol. 16, no. 2, pp. 99–113, Jun. 2002, doi: 10.1207/S15389286AJDE1602_4.
- [19] M. G. Moore and G. Kearsley, *Distance education: A systematic view of online learning*, 3rd ed. Belmont, VA: Wadsworth Cengage Learning, 2012.
- [20] J. C. Roca, C.-M. Chiu, and F. J. Martínez, "Understanding e-learning continuance intention: An extension of the Technology Acceptance Model," *Int. J. Hum.-Comput. Stud.*, vol. 64, no. 8, pp. 683–696, Aug. 2006, doi: 10.1016/j.ijhcs.2006.01.003.
- [21] B. B. Lockee, "Online education in the post-COVID era," *Nat. Electron.*, vol. 4, no. 1, pp. 5–6, Jan. 2021, doi: 10.1038/s41928-020-00534-0.
- [22] M. Maqableh and M. Alia, "Evaluation online learning of undergraduate students under lockdown amidst COVID-19 Pandemic: The online learning experience and students' satisfaction," *Child. Youth Serv. Rev.*, vol. 128, p. 106160, Sep. 2021, doi: 10.1016/j.childyouth.2021.106160.
- [23] A. Patricia Aguilera-Hermida, "College students' use and acceptance of emergency online learning due to COVID-19," *Int. J. Educ. Res. Open*, vol. 1, p. 100011, 2020, doi: 10.1016/j.ijedro.2020.100011.
- [24] N. Avsheniuk, N. Seminikhyna, T. Svyrydiuk, and O. Lutsenko, "ESP Students' Satisfaction with Online Learning during the COVID-19 Pandemic in Ukraine,"

Arab World Engl. J., no. 1, pp. 222–234, Apr. 2021, doi: 10.24093/awej/covid.17.

- [25] M. Curelaru, V. Curelaru, and M. Cristea, “Students’ Perceptions of Online Learning during COVID-19 Pandemic: A Qualitative Approach,” *Sustainability*, vol. 14, no. 13, p. 8138, Jul. 2022, doi: 10.3390/su14138138.
- [26] L. Zizka and G. Probst, “Learning during (or despite) COVID-19: business students’ perceptions of online learning,” *Qual. Assur. Educ.*, Mar. 2022, doi: 10.1108/QAE-12-2021-0188.
- [27] M. Bączek, M. Zagańczyk-Bączek, M. Szpringer, A. Jaroszyński, and B. Woźakowska-Kapłon, “Students’ perception of online learning during the COVID-19 pandemic,” *Medicine (Baltimore)*, vol. 100, no. 7, p. e24821, Feb. 2021, doi: 10.1097/MD.00000000000024821.
- [28] P. Shrivastava, N. Siju, and A. Madbouly, “Project Management Students’ Perception on E-Learning,” in *2021 International Conference on Software Engineering & Computer Systems and 4th International Conference on Computational Science and Information Management (ICSECS-ICOCSIM)*, Aug. 2021, pp. 155–160. doi: 10.1109/ICSECS52883.2021.00035.
- [29] R. N. Laili and M. Nashir, “Higher Education Students’ Perception on Online Learning during Covid-19 Pandemic,” *EDUKATIF J. ILMU Pendidik.*, vol. 3, no. 3, pp. 689–697, Apr. 2021, doi: 10.31004/edukatif.v3i3.422.

- [30] B. Landrum, J. Bannister, G. Garza, and S. Rhame, "A class of one: Students' satisfaction with online learning," *J. Educ. Bus.*, vol. 96, no. 2, pp. 82–88, Feb. 2021, doi: 10.1080/08832323.2020.1757592.
- [31] A. S. N. Agung and M. W. Surtikanti, "Students' Perception of Online Learning during COVID-19 Pandemic: A Case Study on the English Students of STKIP Pamane Talino," *SOSHUM J. Sos. Dan Hum.*, vol. 10, no. 2, pp. 225–235, Jul. 2020, doi: 10.31940/soshum.v10i2.1316.
- [32] A. Seffah, M. Donyaee, R. B. Kline, and H. K. Padda, "Usability measurement and metrics: A consolidated model," *Softw. Qual. J.*, vol. 14, no. 2, pp. 159–178, Jun. 2006, doi: 10.1007/s11219-006-7600-8.
- [33] J.-H. Wu and Y.-M. Wang, "Measuring KMS success: A respecification of the DeLone and McLean's model," *Inf. Manage.*, vol. 43, no. 6, pp. 728–739, Sep. 2006, doi: 10.1016/j.im.2006.05.002.
- [34] N. Almusharraf and S. Khahro, "Students Satisfaction with Online Learning Experiences during the COVID-19 Pandemic," *Int. J. Emerg. Technol. Learn. IJET*, vol. 15, no. 21, p. 246, Nov. 2020, doi: 10.3991/ijet.v15i21.15647.
- [35] L. A. Fiorini, A. Borg, and M. Debono, "Part-time adult students' satisfaction with online learning during the COVID-19 pandemic," *J. Adult Contin. Educ.*, p. 147797142210826, Apr. 2022, doi: 10.1177/14779714221082691.

- [36] N. K. Ibrahim *et al.*, “Medical students’ acceptance and perceptions of e-learning during the Covid-19 closure time in King Abdulaziz University, Jeddah,” *J. Infect. Public Health*, vol. 14, no. 1, pp. 17–23, Jan. 2021, doi: 10.1016/j.jiph.2020.11.007.
- [37] M. S. A. Mansor and A. Ismail, “Learning Styles and Perception of Engineering Students Towards Online Learning,” *Procedia - Soc. Behav. Sci.*, vol. 69, pp. 669–674, Dec. 2012, doi: 10.1016/j.sbspro.2012.11.459.
- [38] N. A. I. C. Mut, N. M. Zain, and M. I. Mohd, “Challenges and Perceptions of E-Learning among Students in A Private Institution: A Case Study in Malaysia,” in *2020 Sixth International Conference on e-Learning (econf)*, Dec. 2020, pp. 166–170. doi: 10.1109/econf51404.2020.9385506.
- [39] T. Muthuprasad, S. Aiswarya, K. S. Aditya, and G. K. Jha, “Students’ perception and preference for online education in India during COVID -19 pandemic,” *Soc. Sci. Humanit. Open*, vol. 3, no. 1, p. 100101, 2021, doi: 10.1016/j.ssaho.2020.100101.
- [40] N. A. Nor Shaid, F. M. Kamruzaman, and N. A. Sulaiman, “Online Learning During Ongoing Covid-19 Pandemic: A Survey of Students’ Satisfaction,” *Int. J. Acad. Res. Bus. Soc. Sci.*, vol. 11, no. 7, Jul. 2021, doi: 10.6007/IJARBSS/v11-i7/10557.

- [41] C. S. PUNLA and R. C. FARRO, “Are We There Yet?: An Analysis of the Competencies of BEED Graduates of BPSU-DC,” *Int. Multidiscip. Res. J.*, vol. 4, no. 3, pp. 50–59, Sep. 2022, doi: 10.54476/ioer-imrj/86523.
- [42] P. Thach, P. Lai, V. Nguyen, and H. Nguyen, “Online learning amid Covid-19 pandemic: students’ experience and satisfaction,” *J. E-Learn. Knowl. Soc.*, vol. 17, no. 1, pp. 39–48, 2021.
- [43] A. Badovinac *et al.*, “The Impact of the COVID-19 Pandemic on Dental Education: An Online Survey of Students’ Perceptions and Attitudes,” *Dent. J.*, vol. 9, no. 10, Art. no. 10, Oct. 2021, doi: 10.3390/dj9100116.
- [44] M. Al-Nasa’h, L. Al-Tarawneh, F. M. A. Awwad, and I. Ahmad, “Estimating students’ online learning satisfaction during COVID-19: A discriminant analysis,” *Heliyon*, vol. 7, no. 12, p. e08544, Dec. 2021, doi: 10.1016/j.heliyon.2021.e08544.
- [45] E. Agyeiwaah, F. Badu Baiden, E. Gamor, and F.-C. Hsu, “Determining the attributes that influence students’ online learning satisfaction during COVID-19 pandemic,” *J. Hosp. Leis. Sport Tour. Educ.*, vol. 30, p. 100364, Jun. 2022, doi: 10.1016/j.jhlste.2021.100364.
- [46] T. Volery and D. Lord, “Critical success factors in online education,” *Int. J. Educ. Manag.*, vol. 14, no. 5, pp. 216–223, Sep. 2000, doi: 10.1108/09513540010344731.

- [47] S. A. Arain *et al.*, “Medical Students and Faculty Perceptions About Online Learning During COVID-19 Pandemic: Alfaisal University Experience,” *Front. Public Health*, vol. 10, Jun. 2022, doi: 10.3389/fpubh.2022.880835.

- [48] E. Gyimah, “Online Learning Engagement and Satisfaction of First Year Undergraduate Students in a Blended Course,” in *2019 International Conference on Mechatronics, Remote Sensing, Information Systems and Industrial Information Technologies (ICMRSISIIT)*, Dec. 2019, pp. 1–6. doi: 10.1109/ICMRSISIIT46373.2020.9405837.

- [49] S. Viola, E. Saeki, and E. Hendricker, “Distance Education in Graduate Training Programs: Lessons Learned from School Psychology Students,” *J. Educ. Online*, vol. 16, Jul. 2019, doi: 10.9743/JEO.2019.12.2.12.

- [50] I. Alqudah, M. Barakat, S. M. Muflih, and A. Alqudah, “Undergraduates’ perceptions and attitudes towards online learning at Jordanian universities during COVID-19,” *Interact. Learn. Environ.*, pp. 1–18, Dec. 2021, doi: 10.1080/10494820.2021.2018617.

- [51] D. Price Banks and S. M. Vergez, “Online and In-Person Learning Preferences during the COVID-19 Pandemic among Students Attending the City University of New York,” *J. Microbiol. Biol. Educ.*, vol. 23, no. 1, Apr. 2022, doi: 10.1128/jmbe.00012-22.

- [52] S. Bali and M. C. Liu, “Students’ perceptions toward online learning and face-to-face learning courses,” *J. Phys. Conf. Ser.*, vol. 1108, p. 012094, Nov. 2018, doi: 10.1088/1742-6596/1108/1/012094.
- [53] V. Drašler, J. Bertoneclj, M. Korošec, T. Pajk Žontar, N. Poklar Ulrih, and B. Cigić, “Difference in the Attitude of Students and Employees of the University of Ljubljana towards Work from Home and Online Education: Lessons from COVID-19 Pandemic,” *Sustainability*, vol. 13, no. 9, Art. no. 9, Jan. 2021, doi: 10.3390/su13095118.
- [54] R. Khalil *et al.*, “The sudden transition to synchronized online learning during the COVID-19 pandemic in Saudi Arabia: a qualitative study exploring medical students’ perspectives,” *BMC Med. Educ.*, vol. 20, no. 1, p. 285, Dec. 2020, doi: 10.1186/s12909-020-02208-z.
- [55] H. R. Susila, A. Qosim, and T. Rositasari, “Students’ Perception of Online Learning in Covid-19 Pandemic: A Preparation for Developing a Strategy for Learning from Home,” *Univers. J. Educ. Res.*, vol. 8, no. 11B, pp. 6042–6047, Nov. 2020, doi: 10.13189/ujer.2020.082240.
- [56] Y. Li, N. Nishimura, H. Yagami, and H.-S. Park, “An Empirical Study on Online Learners’ Continuance Intentions in China,” *Sustainability*, vol. 13, no. 2, p. 889, Jan. 2021, doi: 10.3390/su13020889.
- [57] D. Prasetyanto, M. Rizki, and Y. Sunitiyoso, “Online Learning Participation Intention after COVID-19 Pandemic in Indonesia: Do Students Still Make Trips

for Online Class?,” *Sustainability*, vol. 14, no. 4, Art. no. 4, Jan. 2022, doi: 10.3390/su14041982.

- [58] A. Basith, R. Rosmayadi, S. N. Triani, and F. Fitri, “Investigation of Online Learning Satisfaction During COVID 19: In Relation to Academic Achievement,” *J. Educ. Sci. Technol. EST*, pp. 265–275, Nov. 2020, doi: 10.26858/est.v1i1.14803.
- [59] R. Gopal, V. Singh, and A. Aggarwal, “Impact of online classes on the satisfaction and performance of students during the pandemic period of COVID 19,” *Educ. Inf. Technol.*, vol. 26, no. 6, pp. 6923–6947, Nov. 2021, doi: 10.1007/s10639-021-10523-1.
- [60] D. Keržič *et al.*, “Academic student satisfaction and perceived performance in the e-learning environment during the COVID-19 pandemic: Evidence across ten countries,” *PLOS ONE*, vol. 16, no. 10, p. e0258807, Oct. 2021, doi: 10.1371/journal.pone.0258807.
- [61] J. Cavanaugh, S. Jacquemin, and C. Junker, “A look at student performance during the COVID-19 pandemic,” *Qual. Assur. Educ.*, Jun. 2022, doi: 10.1108/QAE-01-2022-0008.
- [62] A. E. Clark, H. Nong, H. Zhu, and R. Zhu, “Compensating for academic loss: Online learning and student performance during the COVID-19 pandemic,” *China Econ. Rev.*, vol. 68, p. 101629, Aug. 2021, doi: 10.1016/j.chieco.2021.101629.

- [63] A. Hashemi, “Effects of COVID-19 on the academic performance of Afghan students’ and their level of satisfaction with online teaching,” *Cogent Arts Humanit.*, vol. 8, no. 1, Jan. 2021, doi: 10.1080/23311983.2021.1933684.
- [64] N. Rodriguez-Planas, “COVID-19 and College Academic Performance: A Longitudinal Analysis,” *SSRN Electron. J.*, 2021, doi: 10.2139/ssrn.3789380.
- [65] M. Sarfraz *et al.*, “Medical Students’ Online Learning Perceptions, Online Learning Readiness, and Learning Outcomes during COVID-19: The Moderating Role of Teacher’s Readiness to Teach Online,” *Int. J. Environ. Res. Public. Health*, vol. 19, no. 6, p. 3520, Mar. 2022, doi: 10.3390/ijerph19063520.
- [66] M. Younas, U. Noor, X. Zhou, R. Menhas, and X. Qingyu, “COVID-19, students satisfaction about e-learning and academic achievement: Mediating analysis of online influencing factors,” *Front. Psychol.*, vol. 13, 2022, Accessed: Nov. 24, 2022. [Online]. Available: <https://www.frontiersin.org/articles/10.3389/fpsyg.2022.948061>
- [67] M. S. Alharbi, A. K. A. Tuwayjiri, and M. J. Alanazi, “Perception of online learning during COVID-19 among medical students in the Qassim region, Saudi Arabia,” *Biosci. Res.*, vol. 18, pp. 33–40, 2021.
- [68] D. D. Bir, “Comparison of Academic Performance of Students in Online Vs Traditional Engineering Course,” *Eur. J. Open Distance E-Learn.*, vol. 22, no. 1, pp. 1–13, Jul. 2019, doi: 10.2478/eurodl-2019-0001.

- [69] R. M. G. Garcia-Castelan, A. Gonzalez-Nucamendi, V. Robledo-Rella, L. Neri, and J. Noguez, "Face-to-face vs. Online learning in Engineering Courses," in *2021 IEEE Frontiers in Education Conference (FIE)*, Oct. 2021, pp. 1–8. doi: 10.1109/FIE49875.2021.9637177.
- [70] Z. K. Tufan, "COVID-19 Diaries of Higher Education during the Shocking Pandemic," *Gazi Med. J.*, vol. 31, no. 2A, May 2020, doi: 10.12996/gmj.2020.61.
- [71] M. Setia, "Methodology series module 3: Cross-sectional studies," *Indian J. Dermatol.*, vol. 61, no. 3, p. 261, 2016, doi: 10.4103/0019-5154.182410.
- [72] M. A. Khan, V. Vivek, M. K. Nabi, M. Khojah, and M. Tahir, "Students' Perception towards E-Learning during COVID-19 Pandemic in India: An Empirical Study," *Sustainability*, vol. 13, no. 1, p. 57, Dec. 2020, doi: 10.3390/su13010057.
- [73] H. A. Omar, E. M. Ali, and S. Belbase, "Graduate Students' Experience and Academic Achievements with Online Learning during COVID-19 Pandemic," *Sustainability*, vol. 13, no. 23, p. 13055, Nov. 2021, doi: 10.3390/su132313055.
- [74] B. G. Tabachnick and L. S. Fidell, *Using multivariate statistics*, 3rd ed. New York: HarperCollins College Publishers, 1996.
- [75] A. Mayers, *Introduction to Statistics and SPSS in Psychology*. Pearson, 2013.

- [76] J. A. GLINER and G. A. MORGAN, "Measurement Reliability," *J. Am. Acad. Child Adolesc. Psychiatry*, vol. 40, no. 4, pp. 486–488, Apr. 2001, doi: 10.1097/00004583-200104000-00019.
- [77] M. Tavakol and R. Dennick, "Making sense of Cronbach's alpha," *Int. J. Med. Educ.*, vol. 2, pp. 53–55, Jun. 2011, doi: 10.5116/ijme.4dfb.8dfd.
- [78] D. George and P. Mallery, *SPSS for Windows Step by Step: A Simple Guide and Reference, 17.0 Update*. Allyn & Bacon, 2010. [Online]. Available: <https://books.google.com.tr/books?id=KS1DPgAACAAJ>
- [79] S. Yan-Li, N. Jiang, K. Pamanee, and J. Sriyanto, "ONLINE LEARNING READINESS AND SATISFACTION DURING COVID-19 PANDEMIC AMONG UNIVERSITY STUDENTS IN FOUR ASIAN COUNTRIES," *J. Nusantara. Stud. JONUS*, vol. 7, no. 2, pp. 245–269, Jun. 2022, doi: 10.24200/jonus.vol7iss2pp245-269.
- [80] C.-Y. Su and Y. Guo, "Factors impacting university students' online learning experiences during the <scp>COVID</scp> -19 epidemic," *J. Comput. Assist. Learn.*, vol. 37, no. 6, pp. 1578–1590, Dec. 2021, doi: 10.1111/jcal.12555.
- [81] R. N. Shindjabuluka, D. O. Ashipala, and G. N. Likando, "COVID-19 as an enabler for enhancing online learning and teaching skills for nurse educators at the University of Namibia: Prospects and challenges," *Health SA Gesondheid*, vol. 27, p. 1727, Feb. 2022, doi: 10.4102/hsag.v27i0.1727.

- [82] P. Zhang and L. Goel, "Is E-Learning for Everyone? An Internal-External Framework of E-Learning Initiatives," *MERLOT J. Online Learn. Teach.*, vol. 7, no. 2, pp. 193–205, 2011.
- [83] K. Mukhtar, K. Javed, M. Arooj, and A. Sethi, "Advantages, Limitations and Recommendations for online learning during COVID-19 pandemic era," *Pak. J. Med. Sci.*, vol. 36, no. COVID19-S4, pp. S27–S31, May 2020, doi: 10.12669/pjms.36.COVID19-S4.2785.
- [84] A. K. Bolatov, T. Z. Seisembekov, A. Z. Askarova, R. K. Baikanova, D. S. Smailova, and E. Fabbro, "Online-Learning due to COVID-19 Improved Mental Health Among Medical Students," *Med. Sci. Educ.*, vol. 31, no. 1, pp. 183–192, Feb. 2021, doi: 10.1007/s40670-020-01165-y.
- [85] Z. Yu, "Sustaining Student Roles, Digital Literacy, Learning Achievements, and Motivation in Online Learning Environments during the COVID-19 Pandemic," *Sustainability*, vol. 14, no. 8, Art. no. 8, Jan. 2022, doi: 10.3390/su14084388.
- [86] H. Yaseen, A. R. Alsoud, M. Nofal, O. Abdeljaber, and A. S. Al-Adwan, "The Effects of Online Learning on Students' Performance: A Comparison Between UK and Jordan Universities," *Int. J. Emerg. Technol. Learn. IJET*, vol. 16, no. 20, p. 4, Oct. 2021, doi: 10.3991/ijet.v16i20.24131.
- [87] K. L. Boardman, S. A. Vargas, J. L. Cotler, and D. Burshteyn, "Effects of Emergency Online Learning during COVID-19 Pandemic on Student

- Performance and Connectedness,” *Inf. Syst. Educ. J.*, vol. 19, no. 4, pp. 23–36, 2021.
- [88] S. Asgharzadehbonab, A. Akkeleş, and H. Ozder, “Students’ Academic Performance and Perceptions towards Online Learning during the COVID-19 Pandemic at a Large Public University in Northern Cyprus,” *Sustainability*, vol. 14, no. 24, p. 16399, Dec. 2022, doi: 10.3390/su142416399.
- [89] S. Hrastinski, “Asynchronous & Synchronous E-Learning,” *Educ. Q.*, vol. 31, no. 4, pp. 51–55, 2008.
- [90] D. R. Garrison and H. Kanuka, “Blended learning: Uncovering its transformative potential in higher education,” *Internet High. Educ.*, vol. 7, no. 2, pp. 95–105, Apr. 2004, doi: 10.1016/j.iheduc.2004.02.001.
- [91] M. Suresh, V. Vishnu Priya, and R. Gayathri, “Effect of e-learning on academic performance of undergraduate students,” *Drug Invent. Today*, vol. 10, no. 9, pp. 1797–1800, Sep. 2018.
- [92] K. Hamdan and A. Amorri, “The Impact of Online Learning Strategies on Students’ Academic Performance,” in *E-Learning and Digital Education in the Twenty-First Century*, M. Mahruf C. Shohel, Ed. IntechOpen, 2022. doi: 10.5772/intechopen.94425.

- [93] J. L. Harris, M. T. Al-Bataineh, and A. Al-Bataineh, "One to One Technology and Its Effect on Student Academic Achievement and Motivation," *Contemp. Educ. Technol.*, vol. 7, no. 4, pp. 368–381, 2016.
- [94] P. Bandyopadhyay, "The Impact of Course Delivery Systems on Student Achievement and Sense of Community: A Comparison of Learning Community versus Stand-Alone Classroom Settings in an Open-Enrollment Inner City Public Community College," ProQuest LLC, 2010.
- [95] M. French, *Fundamentals of Optimization*. Cham: Springer International Publishing, 2018. doi: 10.1007/978-3-319-76192-3.
- [96] M. M. El-Halwagi, Ed., "Overview of optimization," in *Process Systems Engineering*, vol. 7, Academic Press, 2006, pp. 285–314. doi: 10.1016/S1874-5970(06)80012-3.
- [97] B. Elhami, A. Akram, and M. Khanali, "Optimization of energy consumption and environmental impacts of chickpea production using data envelopment analysis (DEA) and multi objective genetic algorithm (MOGA) approaches," *Inf. Process. Agric.*, vol. 3, no. 3, pp. 190–205, Sep. 2016, doi: 10.1016/j.inpa.2016.07.002.
- [98] N. Noguchi and H. Terao, "Path planning of an agricultural mobile robot by neural network and genetic algorithm," *Comput. Electron. Agric.*, vol. 18, no. 2, pp. 187–204, Aug. 1997, doi: 10.1016/S0168-1699(97)00029-X.

- [99] L. TingXiang, Z. ShuWen, W. QuanYuan, and B. WenDong, “Research of Agricultural Land Classification and Evaluation Based on Genetic Algorithm Optimized Neural Network Model,” in *Software Engineering and Knowledge Engineering: Theory and Practice*, Berlin, Heidelberg, 2012, pp. 465–471. doi: 10.1007/978-3-642-25349-2_62.

- [100] Z. Jalali, E. Noorzai, and S. Heidari, “Design and optimization of form and facade of an office building using the genetic algorithm,” *Sci. Technol. Built Environ.*, vol. 26, no. 2, pp. 128–140, Feb. 2020, doi: 10.1080/23744731.2019.1624095.

- [101] L. Li, “The optimization of architectural shape based on Genetic Algorithm,” *Front. Archit. Res.*, vol. 1, no. 4, pp. 392–399, Dec. 2012, doi: 10.1016/j.foar.2012.07.005.

- [102] R. F. Patron, A. Kessaci, and R. M. Botez, “Flight trajectories optimization under the influence of winds using genetic algorithms,” in *AIAA Guidance, Navigation, and Control (GNC) Conference*, American Institute of Aeronautics and Astronautics. doi: 10.2514/6.2013-4620.

- [103] V. Ahuja, R. J. Hartfield, and A. Shelton, “Optimization of hypersonic aircraft using genetic algorithms,” *Appl. Math. Comput.*, vol. 242, pp. 423–434, Sep. 2014, doi: 10.1016/j.amc.2014.05.120.

- [104] R. L. Panadés-Barrueta, E. Martínez-Núñez, and D. Peláez, “Specific Reaction Parameter Multigrid POTFIT (SRP-MGPF): Automatic Generation of Sum-of-

Products Form Potential Energy Surfaces for Quantum Dynamical Calculations,” *Front. Chem.*, vol. 7, 2019, Accessed: Nov. 14, 2022. [Online]. Available: <https://www.frontiersin.org/articles/10.3389/fchem.2019.00576>

[105] T. F. G. G. Cova and A. A. C. C. Pais, “Deep Learning for Deep Chemistry: Optimizing the Prediction of Chemical Patterns,” *Front. Chem.*, vol. 7, 2019, Accessed: Nov. 14, 2022. [Online]. Available: <https://www.frontiersin.org/articles/10.3389/fchem.2019.00809>

[106] F. T. Silva, M. X. Silva, and J. C. Belchior, “A New Genetic Algorithm Approach Applied to Atomic and Molecular Cluster Studies,” *Front. Chem.*, vol. 7, 2019, Accessed: Nov. 14, 2022. [Online]. Available: <https://www.frontiersin.org/articles/10.3389/fchem.2019.00707>

[107] N. R. Sabar, M. Ayob, G. Kendall, and R. Qu, “A honey-bee mating optimization algorithm for educational timetabling problems,” *Eur. J. Oper. Res.*, vol. 216, no. 3, pp. 533–543, Feb. 2012, doi: 10.1016/j.ejor.2011.08.006.

[108] J. Ferrer, F. Chicano, and E. Alba, “Evolutionary algorithms for the multi-objective test data generation problem,” *Softw. Pract. Exp.*, vol. 42, no. 11, pp. 1331–1362, 2012, doi: 10.1002/spe.1135.

[109] Z. Wu, T. He, C. Mao, and C. Huang, “Exam paper generation based on performance prediction of student group,” *Inf. Sci.*, vol. 532, pp. 72–90, Sep. 2020, doi: 10.1016/j.ins.2020.04.043.

- [110] N. Tohidi and S. M. H. Hasheminejad, “MOQAS: Multi-objective question answering system,” *J. Intell. Fuzzy Syst.*, vol. 36, no. 4, pp. 3495–3512, Jan. 2019, doi: 10.3233/JIFS-181364.
- [111] J. Geunes and P. M. Pardalos, Eds., *Supply Chain Optimization*, vol. 98. Boston, MA: Springer US, 2005. doi: 10.1007/b137269.
- [112] J. Józefowska and A. Zimniak, “Optimization tool for short-term production planning and scheduling,” *Int. J. Prod. Econ.*, vol. 112, no. 1, pp. 109–120, Mar. 2008, doi: 10.1016/j.ijpe.2006.08.026.
- [113] A. M. B. Martins, L. M. C. Simões, and J. H. J. O. Negrão, “Optimization of cable-stayed bridges: A literature survey,” *Adv. Eng. Softw.*, vol. 149, p. 102829, Nov. 2020, doi: 10.1016/j.advengsoft.2020.102829.
- [114] E. K. Lee and T.-L. Wu, “Disease diagnosis: optimization-based methodsDisease Diagnosis: Optimization-Based Methods,” in *Encyclopedia of Optimization*, C. A. Floudas and P. M. Pardalos, Eds. Boston, MA: Springer US, 2009, pp. 753–784. doi: 10.1007/978-0-387-74759-0_133.
- [115] A. Bhandari, B. K. Tripathy, K. Jawad, S. Bhatia, M. K. I. Rahmani, and A. Mashat, “Cancer Detection and Prediction Using Genetic Algorithms,” *Comput. Intell. Neurosci.*, vol. 2022, p. e1871841, May 2022, doi: 10.1155/2022/1871841.

- [116] A. Taneda, “Multi-objective optimization for RNA design with multiple target secondary structures,” *BMC Bioinformatics*, vol. 16, no. 1, p. 280, Sep. 2015, doi: 10.1186/s12859-015-0706-x.
- [117] S. Nayak, “Chapter nine - Multiobjective optimization,” in *Fundamentals of Optimization Techniques with Algorithms*, S. Nayak, Ed. Academic Press, 2020, pp. 253–270. doi: 10.1016/B978-0-12-821126-7.00009-7.
- [118] G. Alonso, E. del Valle, and J. R. Ramirez, “5 - Optimization methods,” in *Desalination in Nuclear Power Plants*, G. Alonso, E. del Valle, and J. R. Ramirez, Eds. Woodhead Publishing, 2020, pp. 67–76. doi: 10.1016/B978-0-12-820021-6.00005-3.
- [119] N. Gunantara, “A review of multi-objective optimization: Methods and its applications,” *Cogent Eng.*, vol. 5, no. 1, p. 1502242, Jan. 2018, doi: 10.1080/23311916.2018.1502242.
- [120] M. Ehrgott, *Multicriteria Optimization*. Springer Science & Business Media, 2005.
- [121] D. B. Fogel, “What is evolutionary computation?,” *IEEE Spectr.*, vol. 37, no. 2, pp. 26–32, Feb. 2000, doi: 10.1109/6.819926.
- [122] C. A. Coello Coello, “A Comprehensive Survey of Evolutionary-Based Multiobjective Optimization Techniques,” *Knowl. Inf. Syst.*, vol. 1, no. 3, pp. 269–308, Aug. 1999, doi: 10.1007/BF03325101.

- [123] C. M. Fonseca and P. J. Fleming, “Genetic Algorithms for Multiobjective Optimization: Formulation, Discussion and Generalization,” in *Proceedings of the 5th International Conference on Genetic Algorithms*, San Francisco, CA, USA, 1993, pp. 416–423.
- [124] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” *IEEE Trans. on Evol. Comput. - TEC*, vol. 6, Jan. 2002.
- [125] N. Beume, B. Naujoks, and M. Emmerich, “SMS-EMOA: Multiobjective selection based on dominated hypervolume,” *Eur. J. Oper. Res.*, vol. 181, no. 3, pp. 1653–1669, Sep. 2007, doi: 10.1016/j.ejor.2006.08.008.
- [126] A. Panichella, “An adaptive evolutionary algorithm based on non-euclidean geometry for many-objective optimization,” in *Proceedings of the Genetic and Evolutionary Computation Conference*, New York, NY, USA, Jul. 2019, pp. 595–603. doi: 10.1145/3321707.3321839.
- [127] S. Tung Ngo, J. Jafreezal, G. Hoang Nguyen, and A. Ngoc Bui, “A Genetic Algorithm for Multi-Objective Optimization in Complex Course Timetabling,” in *2021 10th International Conference on Software and Computer Applications*, New York, NY, USA, Jul. 2021, pp. 229–237. doi: 10.1145/3457784.3457821.
- [128] S. T. Ngo, J. B. Jaafar, I. A. Aziz, G. H. Nguyen, and A. N. Bui, “Genetic Algorithm for Solving Multi-Objective Optimization in Examination

- Timetabling Problem,” *Int. J. Emerg. Technol. Learn. IJET*, vol. 16, no. 11, Art. no. 11, Jun. 2021, doi: 10.3991/ijet.v16i11.21017.
- [129] K. Lunn, “Software Development Life Cycle,” in *Software Development with UML*, London: Macmillan Education UK, 2003, pp. 53–68. doi: 10.1007/978-0-230-80419-7_5.
- [130] R. B. Fletcher, L. H. Meyer, H. Anderson, P. Johnston, and M. Rees, “Faculty and Students Conceptions of Assessment in Higher Education,” *High. Educ.*, vol. 64, no. 1, pp. 119–133, Jul. 2012, doi: 10.1007/s10734-011-9484-1.
- [131] D. Hancock, N. Hare, P. Denny, and G. Denyer, “Improving large class performance and engagement through student-generated question banks,” *Biochem. Mol. Biol. Educ.*, vol. 46, no. 4, pp. 306–317, Jul. 2018, doi: 10.1002/bmb.21119.
- [132] A. Littlejohn, Ed., “Assessing question banks,” in *Reusing Online Resources*, 0 ed., Routledge, 2003, pp. 189–199. doi: 10.4324/9780203465677-26.
- [133] R. J. McCowan and S. C. McCowan, “Item Analysis for Criterion-Referenced Tests,” 1999.
- [134] M. Krzic and S. Brown, “Question banks for effective online assessments in introductory science courses,” *Nat. Sci. Educ.*, Oct. 2022, doi: 10.1002/nse2.20091.

- [135] S. Karaman, “Examining the Effects of Flexible Online Exams on Students’ Engagement in E-Learning,” *Educ. Res. Rev.*, vol. 6, pp. 259–264, 2011.
- [136] C. Qian, “Distributed Pareto Optimization for Large-Scale Noisy Subset Selection,” *IEEE Trans. Evol. Comput.*, vol. 24, no. 4, pp. 694–707, Aug. 2020, doi: 10.1109/TEVC.2019.2929555.
- [137] S. Nayak, “Multiobjective optimization,” in *Fundamentals of Optimization Techniques with Algorithms*, Elsevier, 2020, pp. 253–270. doi: 10.1016/B978-0-12-821126-7.00009-7.
- [138] P. Shah, U. Faquih, R. Devkar, and Y. Shahare, “An Intelligent Question Paper Generator using Randomized Algorithm,” *Int. J. Eng. Res. Technol.*, vol. 11, no. 4, Apr. 2022, doi: 10.17577/IJERTV11IS040041.
- [139] “Handling multiple objectives with particle swarm optimization | IEEE Journals & Magazine | IEEE Xplore.” <https://ieeexplore.ieee.org/document/1304847> (accessed Oct. 22, 2022).
- [140] M. Z. bin Mohd Zain, J. Kanesan, J. H. Chuah, S. Dhanapal, and G. Kendall, “A multi-objective particle swarm optimization algorithm based on dynamic boundary search for constrained optimization,” *Appl. Soft Comput.*, vol. 70, pp. 680–700, Sep. 2018, doi: 10.1016/j.asoc.2018.06.022.

- [141] T. Nguyen *et al.*, “Multi-Swarm Optimization for Extracting Multiple-Choice Tests From Question Banks,” *IEEE Access*, vol. 9, pp. 32131–32148, 2021, doi: 10.1109/ACCESS.2021.3057515.

- [142] I. Alaya, C. Solnon, and K. Ghedira, “Ant Colony Optimization for Multi-Objective Optimization Problems,” in *19th IEEE International Conference on Tools with Artificial Intelligence (ICTAI 2007)*, Oct. 2007, vol. 1, pp. 450–457. doi: 10.1109/ICTAI.2007.108.

- [143] D. Liu, J. Wang, and L. Zheng, “Automatic Test Paper Generation Based on Ant Colony Algorithm,” *J. Softw.*, vol. 8, Oct. 2013, doi: 10.4304/jsw.8.10.2600-2606.

- [144] S. Kumar, S. Jain, and H. Sharma, “Genetic Algorithms,” in *Advances in Swarm Intelligence for Optimizing Problems in Computer Science*, Chapman and Hall/CRC, 2018.

- [145] N. Jun, “An Improved Genetic Algorithm for Intelligent Test Paper Generation,” in *2014 7th International Conference on Intelligent Computation Technology and Automation*, Oct. 2014, pp. 72–75. doi: 10.1109/ICICTA.2014.25.

- [146] Z. Jia, C. Zhang, and H. Fang, “The research and application of general item bank automatic test paper generation based on improved genetic algorithms,” in *2011 IEEE 2nd International Conference on Computing, Control and Industrial*

Engineering, Aug. 2011, vol. 1, pp. 14–18. doi: 10.1109/CCIENG.2011.6007945.

- [147] K. Zhang and L. Zhu, “Application of improved genetic algorithm in automatic test paper generation,” in *2015 Chinese Automation Congress (CAC)*, Nov. 2015, pp. 495–499. doi: 10.1109/CAC.2015.7382551.
- [148] D. Liu, L. Zheng, X. Wang, and S. Zhuan, “Research on Intelligent Test Paper Generation Based on Improved Genetic Algorithm,” in *Proceedings of the 2010 Second WRI Global Congress on Intelligent Systems - Volume 02*, USA, Dec. 2010, pp. 363–365. doi: 10.1109/GCIS.2010.34.
- [149] S. Yan and Y. Guoxing, “A genetic algorithm of test paper generation,” in *2013 8th International Conference on Computer Science & Education*, Apr. 2013, pp. 897–901. doi: 10.1109/ICCSE.2013.6554038.
- [150] Y. Zhou, Y. Li, and C. Feng, “Research on intelligent test paper auto-generating algorithm based on improved GA,” in *2009 Chinese Control and Decision Conference*, 2009, pp. 3938–3942. doi: 10.1109/CCDC.2009.5191989.
- [151] D. V. K. Khanh, P. Vasant, I. Elamvazuthi, and V. N. Dieu, “Multi-Objective Optimization of Two-Stage Thermo-Electric Cooler Using Differential Evolution: MO Optimization of TEC Using DE,” *Handbook of Research on Computational Simulation and Modeling in Engineering*, 2016. <https://www.igi-global.com/chapter/multi-objective-optimization-of-two-stage-thermo-electric-cooler-using-differential-evolution/www.igi->

global.com/chapter/multi-objective-optimization-of-two-stage-thermo-electric-cooler-using-differential-evolution/137437 (accessed Oct. 23, 2022).

- [152] Z. Hu and C. Xing, “An Intelligent Test Paper Generation Method Based on Genetic Particle Swarm Optimization,” in *2016 13th Web Information Systems and Applications Conference (WISA)*, Sep. 2016, pp. 188–194. doi: 10.1109/WISA.2016.46.
- [153] Z. Lou, “An Intelligent Teaching Test Paper Generation System Based on Ant Colony Hybrid Genetic Algorithms,” in *2021 13th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)*, Jan. 2021, pp. 467–470. doi: 10.1109/ICMTMA52658.2021.00107.
- [154] J. Yang, “Design on Generating Test Paper Based on Simulated Annealing Algorithm,” 2015. doi: 10.2991/cmcs-15.2015.186.
- [155] T. Nguyen *et al.*, “Multiple-objective optimization applied in extracting multiple-choice tests,” *Eng. Appl. Artif. Intell.*, vol. 105, p. 104439, Oct. 2021, doi: 10.1016/j.engappai.2021.104439.
- [156] L. M. Crocker and J. Algina, *Introduction to classical and modern test theory*. New York: Holt, Rinehart, and Winston, 1986.
- [157] P. S. Efraimidis and P. G. Spirakis, “Weighted random sampling with a reservoir,” *Inf. Process. Lett.*, vol. 97, no. 5, pp. 181–185, Mar. 2006, doi: 10.1016/j.ipl.2005.11.003.

- [158] J. Blank and K. Deb, “Pymoo: Multi-Objective Optimization in Python,” *IEEE Access*, vol. 8, pp. 89497–89509, 2020, doi: 10.1109/ACCESS.2020.2990567.

- [159] N. A. Zolpakar, S. S. Lodhi, S. Pathak, and M. A. Sharma, “Application of Multi-objective Genetic Algorithm (MOGA) Optimization in Machining Processes,” in *Optimization of Manufacturing Processes*, K. Gupta and M. K. Gupta, Eds. Cham: Springer International Publishing, 2020, pp. 185–199. doi: 10.1007/978-3-030-19638-7_8.

- [160] B. L. Miller and D. Goldberg, “Genetic Algorithms, Tournament Selection, and the Effects of Noise,” *Complex Syst*, 1995, Accessed: Jan. 04, 2023. [Online]. Available: <https://www.semanticscholar.org/paper/Genetic-Algorithms%2C-Tournament-Selection%2C-and-the-Miller-Goldberg/df6ee94e2cf14c38e9cff4d2446a50db0aedd4ca>

- [161] S. N. Sivanandam and S. N. Deepa, *Introduction to genetic algorithms*. Berlin ; New York: Springer, 2007.

APPENDICES

Appendix A: Survey Details

5/28/22, 12:01 PM

EMU Survey - Students' perception of online learning during the COVID-19 pandemic

Students' perception of online learning during the COVID-19 pandemic

A survey study of Eastern Mediterranean University students

Dear Student, In March of 2020, the Eastern Mediterranean University declared a state of epidemic emergency, which resulted in the suspension of face-to-face learning in the university. This survey is part of PhD thesis research about students' perception of online learning during the COVID-19 pandemic in the eastern mediterranean university. We developed this survey to check your opinion of e-learning during the pandemic. We hope that results from this study will help improve quality of online education in the future and will facilitate implementation of e-learning in the curriculum. Participation in this survey is voluntary and anonymous.

There are 30 questions in this survey.

Basic demographics

In the first part of the survey we would like you to describe your basic demographics, IT skills and experience in e-learning.

What is your age group?

● Choose one of the following answers

Please choose **only one** of the following:

- ☐ 18 years and below
- ☐ 19-29
- ☐ 30-39
- ☐ 40-49
- ☐ 50-59
- ☐ 60 years and above

5/28/22, 12:01 PM

EMU Survey - Students' perception of online learning during the COVID-19 pandemic

What faculty or school do you study at?

● Choose one of the following answers

Please choose **only one** of the following:

- ☐ Architecture
- ☐ Art & Science
- ☐ Business & Economics
- ☐ Communication and Media Studies
- ☐ Dentistry
- ☐ Education
- ☐ Engineering
- ☐ Health Sciences
- ☐ Law
- ☐ Medicine
- ☐ Pharmacy
- ☐ Tourism
- ☐ Computing and Technology

What level of education are you studying?

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Undergraduate
- ☐ Master
- ☐ PhD

How would you describe your IT skills?

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ High
- ☐ Moderate
- ☐ Low

Have you ever participated in any type of e-learning before the covid-19 pandemic?

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Yes
- ☐ No

Student's online learning satisfaction

It was accessible from all devices (PC, Mobile, Tablet...)

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

It was flexible on time and space

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

The Materials was presented well

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Learning contents was updated

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

It was possible to co-working with other students

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Learning resources was accessible

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

There was good interaction between student and instructors

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Assessments submit procedure was simple and reliable (Exams, Quizzes, Homeworks,...)

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Assessments was effective (Exams, Quizzes, Homeworks,...)

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

The system prepared useful and accurate educational reports

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Student's preferences on online and face to face learning

Online learning are more flexible on time.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Online learning are more flexible on space.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Online learning resources are more accessible.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Online learning has better structured classes.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Teacher-Student interaction is better in online learning.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Delivery of contents are better in online learning.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Online learning tools provide better perception.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Assessments are better in online learning. (Exams, Quizzes, Homeworks,...)

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Online learning tools provides reports more detailed and comprehensive.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Online learning increase motivation and passion to learn.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Continuance intention of students to use online learning

I intend to continue of using online learning as learning contents delivery method.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

I intend to continue of using online learning for assessment. (Exams, Quizzes, Homeworks,...)

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

I intend to continue of using online learning as interactive communication tool between students and instructors.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

I intend to continue of using online learning as resource sharing space.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

I intend to continue of using online learning in blended mode to assist my face to face learning.

❶ Choose one of the following answers

Please choose **only one** of the following:

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly Agree

Appendix B: Question Bank System Source Codes

The codes used in the question bank system are available in the QuestionBankSystem repository on GitHub at <https://github.com/blue-owner/QuestionBankSystem>. These codes will be made publicly available upon the publication of this thesis and can be accessed by anyone with a GitHub account. The codes are provided as-is, and no support or warranty is implied. Users are responsible for understanding and complying with the terms of use and license agreement for the code.

Appendix C: The Research and Publication Ethics Board Approval



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Bilimsel Araştırma ve Yayın Etiği Kurulu (BAYEK) / Board of Scientific Research and Publication Ethics

Reference No: ETK00-2021-0117

27.12.2021

Subject: Your application for ethical approval.

Re: Saeid Asgharzadeh Bonab

Faculty of Arts and Sciences

EMU's Scientific Research and Publication Ethics Board (BAYEK) has approved the decision of the Ethics Board of Engineering (27.12.2021 date and 2021/ 4) granting Saeid Asgharzadeh Bonab from the Faculty of Arts and Sciences to pursue his PhD article titled **"Students' perception of online learning in Eastern Mediterranean University during the COVID-19 pandemic."** supervised by Assoc. Prof. Dr. Arif Akkeleş.

Best Regards



Prof. Dr. Yücel Vural

Chair, Board of Scientific Research and Publication Ethics - EMU

YV/ck.

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